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The Role of Artificial Intelligence in Enhancing Corrosion Inhibitor Application in Oil and Gas Facilities

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ABSTRACT: Corrosion poses a major challenge to oil and gas facilities. While chemical inhibitors are widely used for mitigation, their effectiveness depends on complex, nonlinear interactions among temperature, pressure, fluid chemistry, material properties, microbial activity, and flow conditions. Traditional selection and dosage approaches, relying on lab tests, empirical models, and periodic inspections, often fail to adapt to dynamic operating environments. Artificial Intelligence (AI), especially machine learning and data-driven optimization offers powerful opportunities to transform corrosion inhibitor management by extracting insights from lab, sensor, inspection, and operational datasets. This review analyzes some artificial intelligence applications throughout the entire inhibitor life cycle: corrosion-rate forecasting, inhibitor selection, dosage optimization, molecular screening and the design of green inhibitors. The discussion focused on use cases like real-time monitoring, predictive maintenance and digital-twin-enabled asset integrity management. Additionally, core AI algorithms such as neural networks, Support Vector Machines (SVMs), Random Forests (RF), Gradient Boosting (GBM), genetic algorithms, fuzzy logic and reinforcement learning, together with more application-oriented QSAR modelling and physics-informed hybrid approaches were assessed. Nonetheless, there are significant barriers to industrial adoption, including data shortage and heterogeneity, interpretability of models, transferability from laboratory scale to field conditions, cybersecurity concerns, as well as a lack of validation under field conditions. To address this shortcoming, how data-driven predictive models are integrated with the experiment must be a prime focus of future research, with standardized datasets and interpretable or physics-based guided AI systems, IIoT integration, experimentally validated closed-loop systems, etc. In the end, AI is a decision-support tool, and when combined with effective engineering mitigations, it can make inhibitor applications more efficient, adaptive, and sustainable.

KEYWORDS: Artificial Intelligence, Corrosion Inhibitors, Machine Learning, Oil And Gas Facilities, Corrosion Monitoring, Dosage Optimization.

1. INTRODUCTION

Metallic infrastructure in the oil and gas industry, from production tubing and flowlines to separators, heat exchangers, and storage tanks, is critical for operational safety and environmental protection. These components are exposed to harsh chemical and physical conditions that can greatly accelerate the degradation of the materials, as Revie and Uhlig [1] point out. Aggressive compounds such as carbon dioxide (CO₂), hydrogen sulfide (H₂S), chlorides, organic acids, and microorganisms are routinely transported by well fluids. Furthermore, work by Imran *et al.* [2] demonstrated how operational factors, which include fluid velocity, multiphase flow dynamics, pressure, and temperature, interact with these corrosive species to dictate actual degradation rates in the field.

Beyond immediate physical damage like wall thinning and localized pitting, unmitigated corrosion poses severe operational and environmental risks, including structural cracking, catastrophic equipment failure, and hazardous hydrocarbon leaks. According to financial assessment benchmarks published by NACE [3], the economic impact of this degradation is staggering, eating up an estimated 3% to 4% of global gross domestic product each year. Consequently, proactive corrosion control forms the backbone of modern asset integrity programs, a role that becomes even more critical as operators manage aging assets alongside harsher production fluids, rising water cuts, and higher acid-gas concentrations.

Among available corrosion control strategies, chemical inhibitors remain widely used because they can be deployed without extensive retrofitting of existing facility infrastructure. Depending on their chemical formulation and primary mechanism, these additives mitigate degradation by adsorbing onto the metal surface to form a protective barrier, altering anodic or cathodic reaction kinetics, or stabilizing oxide layers. But the efficacy of inhibitors seldom depends on dosage alone. Ahmed *et al.* [4] demonstrated that the adsorption kinetics and film longevity were directly impacted by harsh environmental parameters such as operating temperatures, system pressures, or immersion time. Shwetha *et al.* Localized fluid chemistry, including pH, water cut and microbially influenced corrosion, is shown to interact with flow regimes and material properties to affect generic film stability according to [5].

Finding inhibitor type and dosage for the right balance of chemical efficiency and cost is an engineering imponderable [6]. An over-dosing of chemical additives results in increased operating costs and higher environmental impact [6, 7], while an under-dosing leaves the assets exposed to environmental damage [7, 8]. Historically, industry practice has been to rely on laboratory screening, electrochemical testing (e.g., corrosion coupons), field monitoring data, together with empirical rules of thumb. Although these standard approaches are essential for life sciences, research suggests that traditional systems face the challenge of dynamic processing and interpretability of large-scale and semi-structured data generated from current field operations [9].

The digitalization of oil and gas facilities is underway, creating tremendous opportunities for data-driven corrosion management. Modern upstream and midstream operations aggregate vast amounts of historical data spanning real-time process sensors, fluid analyses, thickness measurements, and historical chemical dosing logs. To process these complex, high-dimensional datasets, recent work by Imran *et al.* [2] demonstrated how machine learning algorithms such as deep neural networks and ensemble methods can map intricate, non-linear correlations between operational variables and metal loss rates. Building on these predictive capabilities, Riyaz *et al.* [10] showed how AI-driven frameworks enable dynamic dosage optimization, early anomaly detection, and real-time predictive maintenance strategies.

Beyond operational monitoring, artificial intelligence is revolutionizing the computational design of chemical inhibitors. Rather than relying on slow, empirical trial-and-error laboratory screening, machine-learning-based Quantitative Structure Activity Relationship (QSAR) models predict inhibitor efficiency directly from molecular structure. Özkan *et al.* [11] showed that the integration of QSAR modeling with quantum-chemical calculations, including Density Functional Theory (DFT) and molecular dynamics, has been shown to allow for virtual screening of candidate molecules before these are synthesised. This hybrid computational approach is especially useful for finding environmentally friendly "green" inhibitors, in which important performance-based metrics and environmental safety profiles can be evaluated via *in silico* methods prior to potentially expensive experimental work [12-13].

The convergence of artificial intelligence with Industrial Internet of Things (IIoT) frameworks, real-time sensing, and digital twin technology offers a promising route toward proactive, closed-loop corrosion management. By combining continuous stream data from Electrical Resistance (ER) probes, Linear Polarization Resistance (LPR) sensors, ultrasonic thickness monitors, and process instrumentation into AI models, operators can detect sudden corrosive upsets and trigger swift field interventions. Furthermore, as demonstrated in recent digital twin architectures, integrating these operational streams into a virtual model of physical assets allows engineers to simulate and evaluate competing chemical treating strategies under changing process conditions before committing capital or chemical volumes in the field [2].

Nevertheless, significant practical hurdles hinder widespread field deployment. A critical limitation is that many published AI models rely on small, bench-scale laboratory datasets that fail to capture the chaotic multiphase hydrodynamics, sour gas conditions, and operational variability of real-world production streams [9]. Model transferability is further complicated by severe data imbalance, black-box interpretability concerns, computational overhead, and cybersecurity vulnerabilities inherent to cloud-connected field sensors. Such limitations are especially important in high-consequence scenarios where an AI system's recommendation determines the functioning of a chemical injection pump, the emergency shut-in logic or structural integrity decisions [14-16].

Existing literature provides high-level reviews with regard to the use of AI in general metallurgy, molecular modeling or approaches related to structural inspection, but a major gap is how these computational tools enable an end-to-end corrosion inhibitor lifecycle. To address this, we present a holistic review detailing the entire inhibitor management workflow from *in silico* molecular screening and performance prediction to dynamic dosage optimization, real-time IIoT monitoring, and finally the dream of semi-autonomous chemical management systems.

This review aims to close these operational gaps by examining the deployment of artificial intelligence (AI) and machine learning (ML) in the chemical corrosion control programming throughout oil and gas facilities. From the essential concepts of oilfield corrosion and inhibition, we discuss the use of computational architectures from QSAR algorithms to physics-informed machine learning (PIML) in inhibitor selection, dosage optimization, green molecule discovery, and digital-twin-based asset management. Crucially, rather than treating AI as a black box, this work places special emphasis on practical field deployment challenges, including laboratory-to-field model transferability [9], data sparsity, and model interpretability. Finally, we map out future research trajectories, focusing on explainable AI (XAI), standardized benchmark datasets, IIoT integration, and experimentally validated, semi-autonomous chemical management systems capable of safe, real-time industrial operation [2, 10].

2. CORROSION IN OIL AND GAS FACILITIES

Corrosion is still one extremely common and expensive threat to oil and gas infrastructure worldwide. In this context, whenever metallic components operate under extreme conditions across upstream, midstream and downstream assets, the presence of aggressive species, e.g., carbon dioxide (CO₂), hydrogen sulfide (H₂S), chlorides, organic acids and microbes, etc

will contribute to rapid degradation of the material. As shown by Revie and Uhlig [1], these chemical and biological agents interact dynamically at high pressures, elevated temperatures, and multiphase flow conditions, resulting in complex degradation mechanisms. Consequently, Hughes et al. This is in contrast to [9], who found that empirical models based on typical metal corrosion theory often perform poorly in such complex operational regimes.

While the loss of steel due to uncontrolled corrosion can prove catastrophic, its effects on safety stretch far beyond simple metal loss. These structural failures can result in large-scale uncontrolled hydrocarbon leaks, oil and gas pipeline ruptures, emergency production shut-ins, serious environmental pollution and risks to the lives of our workers. According to financial benchmarks published by NACE [3], corrosion mitigation and failure costs account for 3% enclosing 4% of the global gross domestic product every year, amounting to hundreds of billions in maintenance, remediation, and asset replacement. As water cuts increase throughout the life cycle of mature fields, as sour gas concentrations rise and reservoir conditions become increasingly hostile, proactive corrosion control is becoming more imperative than ever.

Chemical inhibitors still represent the first line of defense among available mitigation strategies, as they offer reliable protection with no need for expensive structural modifications [17–18]. But optimizing the efficiency of inhibitors is seldom easy [17, 8], according to Riyaz et al. The performance of inhibitors relies on complex, nonlinear interactions between thermodynamic conditions, multiphase hydrodynamics, water chemistry, microbial activity, and the concentration of active chemicals at the target site [10]. Because these variables fluctuate dynamically across production assets, traditional dosing strategies often fail to maintain consistent protection. To address this challenge of how to integrate artificial intelligence into field management workflows that allows operators to synthesize complex laboratory and production datasets requires enabling precise corrosion forecasting, automated dosage optimization, and proactive asset integrity management [2].

2.1. MAJOR TYPES OF CORROSION IN OIL AND GAS FACILITIES

Across upstream, midstream, and downstream operations, metallic infrastructure encounters a wide spectrum of corrosion mechanisms (FIGURE 1), each dictated by local operational, metallurgical, and environmental parameters. As outlined by Revie and Uhlig [1], uniform (general) corrosion causes relatively even metal thinning across exposed surfaces. While its predictable rate makes it less prone to sudden catastrophic failure, progressive wall loss over time severely compromises the structural integrity of carbon-steel storage tanks, pressure vessels, and transport pipelines handling CO₂-bearing fluids.

More sophisticated and limited attack mechanisms, on the other hand, have a much greater operational risk by virtue of their ability to stop at relatively fast penetration rates while also being difficult for data analysts to detect. Pitting corrosion initiates with local breakdown of passive surface films, induced mainly by the accumulation of chloride and stagnant conditions, where deep cavities are created while a surrounding surface remains intact or minimally affected [19]. This can cause serious integrity issues for offshore separators, heat exchangers and subsea pipelines. Crevice corrosion, which also has an analogous localized mechanism, develops in micro-environmental and restricted geometry environments, including gasket seats, bolted flanges, under-deposit zones, etc., where differential aeration cells drive rapid metal dissolution occurring within subsea configurations [1]. Modes of environmental degradation by production streams: what chemical species are in the way.

CO₂ (Sweet) Corrosion — Dissolved CO₂ combines with H₂O to produce carbonic acid H₂CO₃, which will decrease the pH and thus enhance the iron oxidation process. Despite the fact that protective iron carbonate (FeCO₃) scales can form in order to inhibit corrosion, Nesic [20] shows that high fluid velocities and wall shear stress rapidly remove these films, exposing a clean metal surface for renewed attack, requiring constant addition of inhibitors.

H₂S (Sour) Corrosion: In sour service, the presence of hydrogen creates catastrophic hydrogen embrittlement mechanisms with surface loss. According to Kermani and Morshed [21], the absorption of atomic hydrogen into susceptible high-strength steels leads to failure in the form of SSSC, Hydrogen-Induced Cracking (HIC) and Stress-Oriented HIC SOHIC.

Microbiologically Influenced Corrosion (MIC): This includes damage due to biological activity, resulting in severe localized degradation. Javaherdashti [22] reported that biofilms were formed by a complex community of sulfate-reducing bacteria (SRB), acid-producing bacteria (APB) and iron-oxidizing bacteria (IOB) on the walls in pipes. Such biofilms generate corrosive micro-environments in pipelines with slow flow, water injection facilities and storage tanks.

Finally, erosion-corrosion represents a mechanical-electrochemical synergetic failure mode. As detailed by Fontana [23], high-velocity multiphase flow carrying entrained sand or solids physically strips protective oxide and inhibitor films, continually exposing fresh reactive metal. This fluid-dynamic degradation is especially severe at high-turbulence geometries like elbows, chokes, and pumps. Because these 7 mechanisms rarely operate in isolation, field corrosion rates are dictated by complex, non-linear interactions among temperature, pressure, hydrodynamics, water chemistry, microbial populations, and inhibitor kinetics. Capturing these multivariable dynamics exceeds the capability of traditional empirical equations, establishing the clear necessity for artificial intelligence and machine-learning frameworks capable of predictive modeling, molecular screening, and dynamic dosage optimization.



FIGURE 1 Types of Corrosion

2.2. FACTORS INFLUENCING CORROSION AND INHIBITOR APPLICATION IN OIL AND GAS SYSTEMS

Corrosion in oil and gas facilities is governed by the complex interaction of physical, chemical, biological, and operational factors that vary throughout upstream, midstream, and downstream operations. Instead of moving independently, these variables affect each other in a very nonlinear manner, and thus the corrosion behaviour becomes hard to estimate under changing field conditions. Comprehensive knowledge of these interactive responses is crucial for identifying suitable corrosion inhibitors and creating efficient data-centric corrosion management solutions [1, 10]. Temperature is one of the most critical parameters affecting corrosion as it enhances electrochemical reactions, affects reaction kinetics, and has an impact on the adsorption efficiency and thermal stability of corrosion inhibitors. High temperatures typically found in deep reservoirs, geothermal wells, and refinery process units may also disrupt protective corrosion product films and decrease inhibitor effectiveness, thus increasing corrosion rates unless thermally stable inhibitor formulations are used [4]. The effect of pressure is also important due to the change in solubility for corrosive gases like carbon dioxide (CO_2) and hydrogen sulfide (H_2S). With higher pressure, more of these gases dissolve in produced fluids, forming carbonic and weak sulfur-containing acids, which can enhance the corrosion of carbon steel and other metallic components [24]. Elevated pressure, together with H_2S in sour service conditions, can further lead to sulfide stress cracking and hydrogen-induced damage, which present major asset integrity challenges [1]. The chemical composition of production fluids is another important factor that governs corrosion mechanisms. Chloride ions destabilize passive films and result in localized corrosion initiation, while dissolved O_2 can enhance cathodic reactions and increase the general corrosion rate. Different constituents, like organic acids, dissolved salts, sulfur compounds, production chemicals and suspended solids, promote or inhibit corrosion at certain concentrations and interactions with the metallic surface [5].

Equally significant are flow conditions, as they dictate the transport of corrosive species and the stability of protective inhibitor films—or corrosion products. In many cases, deposits and biofilms are favoured by low flow velocities that lead to under-deposit corrosion as well as microbiologically influenced corrosion (MIC) in metals. On the other hand, excessive flow velocities can erode protective films and expose fresh metal surfaces, leading to accelerated corrosion damage and erosion–corrosion [2]. The production environment's pH conditions also dictate corrosion behavior by influencing the kinetics of electrochemical reactions and passive oxide layer stability. Corrosion processes strongly depend on pH since metal dissolution generally increases with acidic conditions, where stronger corrosion inhibition approaches are required, while alkaline conditions can increase protective surface film formation [4].

Increased recycling of produced water, water flooding and enhanced oil recovery technologies have increased the prevalence of microbiologically influenced corrosion (MIC) in modern oil fields. Biofilms of sulfate-reducing bacteria, acid-producing bacteria and other microorganisms can colonize metal surfaces, produce corrosive metabolites and change local electrochemical conditions, thus enhancing both uniform corrosion and localized corrosion. Effective management of MIC therefore requires the integration of corrosion inhibitors with microbial control strategies and continuous monitoring to minimize infrastructure degradation and operational risks [2, 25]. Table 1 provides factors affecting corrosion and their relevance to inhibitor performance.

Overall, the simultaneous interaction of these environmental and operational variables makes corrosion prediction particularly challenging using conventional empirical approaches. This complexity provides a strong justification for the application of artificial intelligence, which can analyse large and diverse datasets to identify hidden relationships, predict corrosion behaviour, and optimise corrosion inhibitor performance under continuously changing operating conditions [10, 26].

TABLE 1 Variables Governing Corrosion and Inhibitor Performance

Variable	Influence On Corrosion	Relevance To Inhibitor Application
Temperature	Reaction kinetics, film stability	Can alter adsorption and inhibitor degradation
Pressure	CO ₂ /H ₂ S dissolution	Influences corrosive environment
pH	Electrochemical reactions	Affects inhibitor speciation/adsorption
Water chemistry	Ionic environment	Influences corrosion and film stability
Flow regime	Mass transfer/film removal	Influences inhibitor transport and persistence
Fluid composition	Corrosive species and phase behavior	Influences inhibitor compatibility
Inhibitor concentration	Surface coverage	Determines protection level
Microbial activity	Biofilm/metabolites	Can alter corrosion mechanism

2.3. CONSEQUENCES OF CORROSION FOR ASSET INTEGRITY AND INHIBITOR MANAGEMENT

Beyond immediate material loss, unmitigated corrosion carries far-reaching economic, environmental, and safety consequences for oil and gas operations. Direct expenditures such as routine inspection, non-destructive monitoring, structural repair, equipment replacement, and continuous inhibitor injection impose a steady financial burden. However, seminal industry cost studies by Koch *et al.* [3] demonstrated that indirect expenses frequently dwarf direct chemical and repair costs. These tangible hidden costs are driven by deferred production, facility shut-ins, environmental clean-up work, regulatory fines and long-lasting reputational damage. [1] In addition, work presented by Imran *et al.* [2] pointed out that internal corrosion failures in large pipeline networks still lead to catastrophic oil spillage and gas release incidents worldwide, emphasizing the importance of proactive, predictive integrity strategies.

Managing these risks becomes increasingly complex as production infrastructure matures. Aging fields are characteristically plagued by rising water cuts, higher partial pressures of acid gases (CO₂ and H₂S), and intensified microbial activity a harsh combination that rapidly accelerates metal loss [24]. Because operating conditions fluctuate over an asset's lifecycle, fixed-dose chemical treatment programs often prove inefficient, leading to either under-protection or excessive chemical consumption. To overcome these dynamic operational challenges, Toor [26] revealed that the oil and gas sector is actively deploying artificial intelligence (AI) and data-driven frameworks to continuously evaluate corrosion rates, automate inhibitor dosage, and optimize integrity management.

2.4. IMPLICATIONS FOR ARTIFICIAL INTELLIGENCE-BASED CORROSION MANAGEMENT

Oilfield corrosion is dynamic and highly non-linear, which limits the predictive accuracy of empirical models. Riyaz *et al.* [10] noted that conventional correlations fail to account for the simultaneous, coupled interactions of temperature, operating pressure, fluid dynamics and water cut, pH, microbial activity and chemical inhibitor concentrations in changing field environments. Hughes *et al.* [9] demonstrated that Artificial Intelligence (AI) can be trained to correlate heterogeneous data from synthetic datasets including laboratory screening assays, real-time probe signals, process telemetry, and historical inspection logs to identify intricate high-dimensional degradation patterns.

By concurrently processing these multivariate inputs, computational models go beyond simple metal-loss forecasting. Toor [26] demonstrated that AI-driven architectures enable automated inhibitor selection, precise dosage tuning, and dynamic decision support that are tailored to live process conditions. Furthermore, when embedded into Industrial Internet of Things (IIoT) networks and digital twin frameworks, work by Imran *et al.* [2] showed that these predictive engines drive proactive asset integrity management, optimizing chemical consumption, cutting operational downtime, and extending the sustainable lifespan of oil and gas infrastructure [26].

3. CLASSIFICATION, MECHANISMS, SURFACE CHARACTERIZATION AND APPLICATION OF CORROSION INHIBITORS IN OIL AND GAS FACILITIES

Chemical corrosion inhibitors represent the most widely deployed strategy for mitigating internal metal loss across oil and gas facilities, primarily because they can be administered without altering physical plant architecture. Unlike cathodic protection or barrier coatings, inhibitor chemistry is introduced directly into fluid streams, making it ideal for complex subsea manifolds, long-distance transport pipelines, refinery units, and offshore processing topsides. Verma *et al.* [27] emphasized that this high operational flexibility, combined with relatively low capital expenditure, makes chemical treating a cornerstone of modern asset integrity management.

As defined by Jones [19], a corrosion inhibitor is any chemical that, when added to the corrosive medium in low concentrations, significantly decreases metal decomposition rates by disrupting anodic or cathodic electrochemical processes or both at the same time. Formulation optimization entails weighing a number of operational drivers such as fluid composition, partial pressures of acid gases, system metallurgy, hydrodynamic shear stress and environmental discharge regulations.

During field operations, chemical inhibitors can be injected continuously or through periodic batch treatments depending on the system dynamics. Umoren and Solomon [28] explained that continuous dosing is the standard for production tubing,

gathering flowlines, and export pipelines where corrosive water cuts are continuously present. Conversely, batch treatments are routinely applied to storage vessels, stagnant headers, and idle pipelines during shutdown or preservation phases.

3.1. CLASSIFICATION OF CORROSION INHIBITORS

Corrosion inhibitors can be classified according to electrochemical mechanism, chemical composition, mode of adsorption, or method of application. These classification systems are not mutually exclusive; therefore, an inhibitor may belong to more than one category depending on the classification criterion. Understanding these classifications is essential for selecting inhibitors that provide maximum protection under specific operating conditions. Table 2 provides a classification of corrosion inhibitors according to mechanism of action and application.

3.1.1. ANODIC INHIBITORS

Anodic inhibitors reduce corrosion by suppressing the anodic dissolution of metal. Such inhibitors favour the development of stable passive oxide films on the surface and consequently lower the rate at which metal atoms oxidise as ions. Common anodic inhibitors include chromates, nitrites, molybdates, phosphates and silicates [1].

Anodic inhibitors are very effective, but the quantity and control of their use is extremely important because without proper concentration the surface may not be passivated completely and local corrosion like pitting will appear. However, the industrial application of chromate-based inhibitors has been reduced significantly in recent years due to environmental and health concerns, leading to extensive research towards developing environmentally benign alternatives.

3.1.2. CATHODIC INHIBITORS

Cathodic inhibitors decrease corrosion by slowing cathodic reactions, particularly oxygen reduction or hydrogen evolution. These inhibitors either precipitate insoluble compounds on cathodic sites or reduce oxygen diffusion to the metal surface. Common cathodic inhibitors include zinc salts, calcium compounds, polyphosphates, and certain organic molecules capable of forming protective deposits. Because cathodic inhibitors generally do not induce localized corrosion when underdosed, they are often considered safer than anodic inhibitors for field applications [19].

3.1.3. MIXED-TYPE INHIBITORS

Mixed-type inhibitors inhibit mixed types of anodic and cathodic electrochemical reactions at the same time. Providing general-purpose corrosion control over a wide range of operating conditions, they represent the largest class of inhibitors applied in oil and gas production.

This classification consists mainly of commercial oilfield corrosion inhibitors, which contain nitrogen, sulfur, oxygen or phosphorus-containing organic compounds like imidazolines, amines, amides, quaternary ammonium salts and heterocyclic compounds. Adsorption on Metal Surfaces: The donor atoms containing lone-pair electrons of these molecules adsorb onto metal surfaces, and a compact protective film is formed to protect the metal from a corrosive treatment environment [27].

3.2. MECHANISMS OF CORROSION INHIBITION

The effectiveness of corrosion inhibitors depends primarily on their ability to interrupt electrochemical corrosion reactions occurring at the metal-electrolyte interface. Several mechanisms contribute to corrosion inhibition depending on inhibitor chemistry and environmental conditions. Figure 2 provides several mechanisms of corrosion inhibition.

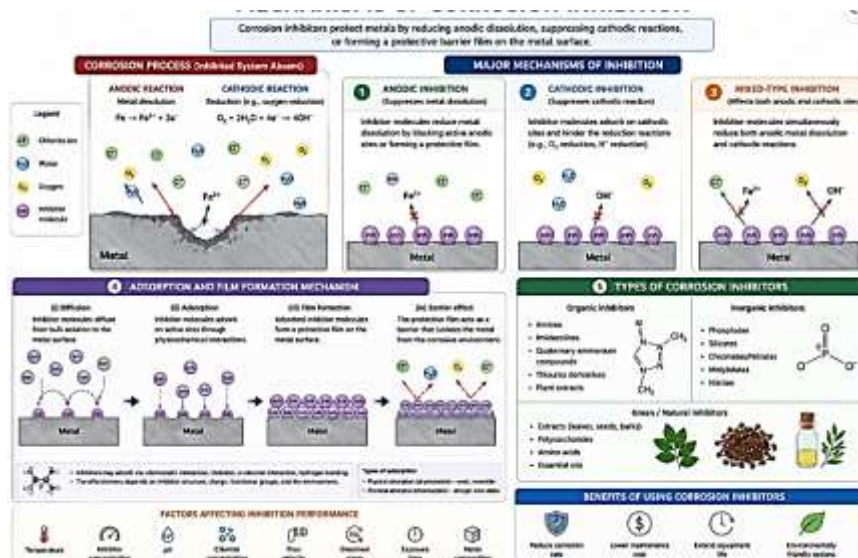


FIGURE 2 Corrosion Inhibitor Mechanisms

TABLE 2 Classification of Corrosion Inhibitors According to Mechanism of Action and Application

Classification	Sub-class	Mechanism of Action	Typical Examples	Major Applications	Advantages	Limitations
Anodic inhibitors	Oxidizing inhibitors	Promote formation of a passive oxide film on anodic sites, thereby reducing metal dissolution [1, 19]	Chromates, nitrites, molybdates	Cooling water systems, reinforced concrete, water treatment	High inhibition efficiency and long-lasting protection [23].	May induce localized corrosion if used below the critical concentration; some compounds are toxic [1].
	Non-oxidizing inhibitors	React with dissolved metal ions to produce insoluble protective compounds on the metal surface [23].	Phosphates, silicates, borates	Boilers, cooling systems	Good passivation characteristics [19].	Require careful dosage control [23].
Cathodic inhibitors	Oxygen scavengers	Remove dissolved oxygen, thereby suppressing the cathodic oxygen reduction reaction [19].	Sodium sulphite, hydrazine	Boiler feed water, steam systems	Effective in deaerated systems [1].	Limited effectiveness where oxygen ingress occurs [19].
	Cathodic poisons	Reduce hydrogen evolution or oxygen reduction reactions at cathodic sites [1].	Zinc salts, polyphosphates	Acid cleaning, industrial cooling systems	Reduce cathodic reaction rates [23].	Often require relatively high concentrations [19].
Mixed-type inhibitors	Organic inhibitors	Simultaneously suppress anodic and cathodic electrochemical reactions through adsorption onto the metal surface [28, 12].	Imidazolines, amines, quaternary ammonium compounds	Oil and gas pipelines, production systems	High inhibition efficiency across diverse environments [27].	Adsorption depends on temperature, pH and fluid chemistry [28].
Organic adsorption inhibitors	Nitrogen-containing compounds	Adsorb through lone-pair electrons on nitrogen atoms, forming a protective molecular film [27].	Pyridine, imidazole, triazoles	Carbon steel, copper alloys	Effective at relatively low concentrations [12].	Performance decreases at elevated temperatures [12].
	Sulphur-containing compounds	Chemisorb through sulphur atoms to form a compact protective layer [12].	Thiourea, mercaptobenzothiazole	Acid pickling, petroleum refining	Excellent protection in acidic environments [28]	Some compounds pose environmental concerns [27]
	Oxygen-containing compounds	Adsorb through oxygen-containing functional groups to reduce active	Alcohols, phenols, carboxylic acids	Mild steel, aluminium alloys	Many are environmentally friendly [27]	Generally exhibit lower inhibition efficiency than nitrogen-containing

		corrosion sites (Umoren and Solomon, 2019).				inhibitors [12]
Green corrosion inhibitors	Plant extracts	Phytochemicals such as alkaloids, flavonoids and tannins adsorb on the metal surface to form a protective film [27, 29]	Neem, ginger, garlic, aloe vera, green tea	Acid media, cooling water systems, oil and gas facilities	Renewable, biodegradable and environmentally benign [29]	Composition varies with plant species, extraction method and geographical location [27]
	Biopolymers	Form barrier films through polymer adsorption and cross-linking [27]	Chitosan, cellulose derivatives, starch	Biomedical devices, protective coatings	Biodegradable and non-toxic [29]	Lower mechanical stability than synthetic polymers [27]
	Amino acids	Coordinate with metal atoms through amino and carboxyl functional groups [28]	Glycine, cysteine, methionine	Acidic environments	Low toxicity and environmentally friendly [27]	Moderate inhibition efficiency in highly aggressive media [28]
Volatile corrosion inhibitors (VCIs)	Vapor-phase inhibitors	Vaporize and condense on metal surfaces to produce a protective molecular film [1, 19]	Dicyclohexylammonium nitrite (DICHAN), cyclohexylamine carbonate	Storage tanks, equipment packaging, enclosed systems		

3.2.1. ADSORPTION MECHANISM

Adsorption is the most common mechanism through which organic corrosion inhibitors protect metallic surfaces. Inhibitor molecules adsorb onto active corrosion sites through physical adsorption (electrostatic interactions), chemical adsorption (coordinate covalent bonding), or a combination of both. Organic molecules containing nitrogen (N), oxygen (O), sulfur (S), phosphorus (P), aromatic rings, and multiple bonds exhibit strong adsorption tendencies because these functional groups possess lone-pair electrons or π -electrons capable of interacting with vacant d-orbitals of metallic atoms [12]. The adsorbed molecules act as a dense layer covering the surface, prohibiting the diffusion of corrosive species like chloride ions, dissolved oxygen, carbon dioxide and hydrogen sulfide. Adsorption isotherms such as the Langmuir adsorption isotherm, Temkin adsorption isotherm, Freundlich adsorption isotherm and Frumkin adsorption isotherm are often used for the description of the adsorption process. The adsorption models help to clarify the inhibitor effectiveness at various concentrations and along with operating conditions.

3.2.2. PASSIVE FILM FORMATION

Certain inorganic corrosion inhibitors can serve as passivators, promoting the formation of stable passive oxide or hydroxide films on metallic surfaces that can effectively prevent corrosion by serving as a barrier between the metal and the corrosive environment. Such passive layers restrict the transport of corrosive species and inhibit the electrochemical processes that promote metal dissolution, thus leading to reduced corrosion rates [24]. The passive films' utility and permanence, on the other hand, are extremely reliant on the environmental operating conditions. The passive layer formation, stability and protection can be affected by pH, temperature, concentration of chloride ions, dissolved oxygen and fluid flow [5]. In extremely aggressive conditions, like those endowed with high concentrations of chloride or dynamically loaded with high flow velocities, such passivation films could become destabilized or ruptured, exposing fresh metal surfaces to localized corrosion types, pitting and crevice corrosion [1]. Therefore, it is crucial to maintain the passivity of films to guarantee prolonged action of inorganic corrosion inhibitors in industrial systems [24].

3.2.3. PRECIPITATION MECHANISM

Some anticorrosive barrier systems in fact operate by reacting with the dissolved ions, driving chlorine or sodium largely throughout the process fluid, since this reaction generates soluble precipitates which progressively solidify on top of your metal surface. Deposits essentially create a barrier that inhibits the electrochemically active sites or limits the diffusion of aggressive species, hence decreasing the metal dissolution rate [5]. Such materials include calcium carbonate, zinc hydroxide and various phosphate compounds, which are widely utilized in cooling water systems and other industrial process devices to improve

corrosion protection and limit corrosion [24]. The mechanism works if it is combined with suitable water conditions such as water chemistry, pH, temperature and ion concentration because these parameters affect the structure, adhesion and stability of the formed protective deposits [4]. Nevertheless, a high amount of precipitate formation may result in scale build-up and cause under-deposit corrosion on pipelines with insufficient water chemistry control [1]; thus, effective inhibitor dosage and optimization of water chemistry are essential to provide efficient corrosion inhibition without consequence on performance.

3.2.4. HYDROPHOBIC BARRIER FORMATION

The effectiveness of self-assembled hydrophobic surface films is a common basis for modern organic corrosion inhibitors. Most of the organic molecules used in self-assembly are amphiphilic, containing a polar "headgroup" that interacts directly with the metallic surface and made up of long hydrocarbon chains forming a hydrophobic "tailgroup" [27]. After initial adsorption onto the metal surface, these non-polar chains orient outwards into bulk solution to form a very dense, water-repellent hydrocarbon barrier across this interface. This hydrophobic shield restricts water penetration, limits oxygen diffusion, and inhibits aggressive ionic species such as chlorides from coming into contact with the underlying metallic substrate, thereby substantially slowing down electrochemical dissolution rates [27, 6].

Establishing this hydrophobic barrier is critical in the oil and gas sector, particularly for imidazoline derivatives and quaternary ammonium salts widely deployed to protect carbon steel production pipelines [29]. Under turbulent flow conditions and harsh multiphase environments where water-in-oil emulsions and dissolved corrosive gases (CO₂ and H₂S) are present the structural integrity and surface packing density of these hydrophobic films dictate the long-term persistence and protection efficiency of chemical treatment programs [6, 30].

3.3. TYPES OF CORROSION INHIBITORS USED IN OIL AND GAS FACILITIES

Several categories of inhibitors have been successfully applied throughout the oil and gas value chain.

3.3.1. ORGANIC CORROSION INHIBITORS

Organic inhibitors remain the dominant class used in petroleum production because of their excellent adsorption properties and compatibility with carbon steel. Common examples are imidazolines, fatty amines, quaternary ammonium compounds, pyridines, Schiff bases, thiourea derivatives, triazoles, amides and amino alcohols. These inhibitors are particularly effective against CO₂ corrosion and are widely used in production tubing, pipelines, separators, and refinery units [28].

3.3.2. INORGANIC CORROSION INHIBITORS

Inorganic corrosion inhibitors comprising ionic compounds such as nitrites, molybdates, phosphates, silicates, and zinc salts have historically played a central role in protecting industrial alloys. Farid *et al.* [31] established that these additives passivate metallic substrates by forming protective oxide films that directly suppress anodic metal dissolution or cathodic reduction kinetics. This passivating capability drastically slows electrochemical corrosion rates across carbon steel and various complex alloys in recirculating infrastructure [32].

Despite their established performance in closed-loop cooling circuits and water treatment systems, the field application of legacy inorganic inhibitors has dropped sharply in recent years. Galleguillos Madrid *et al.* According to [32], the decline is linked to more severe environmental regulations on industrial effluents. A large number of conventional inorganic formulations are characterized by high aquatic toxicity, resistance to natural biodegradation and bioaccumulation in marine habitats, causing long-term ecological risks that are incompatible with new environmental standards.

In response to these regulatory concerns, both the academic and industrial approaches shifted towards developing sustainable green alternatives. Findings from Farid *et al.* [31] demonstrated that present R&D aimed toward developing bio-based and plant-extracted organic formulations that are created to meet or exceed the surface-passivating efficiency of existing inorganic additives while being fully compliant with all international eco-toxicity and biodegradability requirements [32].

3.3.3. GREEN CORROSION INHIBITORS

Growing environmental mandates and sustainability targets have driven significant interest in bio-based, eco-friendly corrosion inhibitors sourced from renewable biomass. The green alternatives synthesized by Verma *et al.* [27] relied on phytochemicals extracted from plant sources such as *Azadirachta indica* (neem), *Moringa oleifera*, *Lawsonia inermis* (henna), and agricultural waste products like citrus peels and tea leaves, which are rich in organic compounds that adsorb onto metal surfaces to block active corrosion sites. In parallel, natural biopolymers including chitosan, modified cellulose, starch, and lignin have emerged as effective film-forming agents. Compared to traditional synthetic formulations, these renewable inhibitors offer markedly lower aquatic toxicity, rapid natural biodegradability, and superior environmental compatibility in sensitive offshore discharge zones.

3.4. FACTORS AFFECTING CORROSION INHIBITOR PERFORMANCE

The performance of corrosion inhibitors is subject to the influence of multiple operational, environmental and chemical variables, which makes inhibitor selection and optimization one of the great challenges in corrosion [5]. Inhibitor protection films on metallic surfaces of a system are significantly influenced by many variables, such as inhibitor concentration, temperature, pressure, fluid velocity, water chemistry and CO₂ and H₂S concentrations [4]; salinity [20]; pH [21]; exposure time; metal surface condition; microbial activity [22]; compatibility with other production chemicals; water cut and flow regime during production [24]. These are generally not independent, and their interplay can be quite complicated, but a large number of corrosion inhibitors show how they affect the behavior of adsorption stability, etc. [11]. Corrosion inhibition is therefore extremely dependent on the combination of insights from the operating environment rather than a single parameter [5]. For example, the increase in concentration of a corrosion inhibitor usually improves corrosion protection to some extent because such compounds promote an adsorbed film covering the metal surface more uniformly and stably [4]. However, this improvement can only be achieved up to an optimum concentration, above which further chemical injection hardly or at all enhances the inhibition efficiency but raises the operational costs significantly [24]. Likewise, temperature can increase or decrease inhibitor performance depending on the chemical nature of the inhibitor and operating conditions. An appropriate temperature rise would favor both adsorption and kinetics of the reaction, resulting in an increase in inhibition efficiency; in contrast, a too-high temperature will benefit the desorption and decomposition of inhibitor molecules while degrading the protective film [4, 5]. Interactions of pressure, fluid flow, salinity and dissolved acid gases have been similarly reported as modifying the electrochemical reactions that actually generate corrosion or the characteristics of absorbable inhibitor molecules [11, 24].

The performance of corrosion inhibitors is therefore governed by highly coupled electrochemical, metallurgical, hydrodynamic, chemical, and biological processes that interact in a nonlinear manner [26]. Changes in one operating parameter often alter the influence of several others, making corrosion behaviour difficult to predict using conventional empirical equations or laboratory observations alone [11]. This challenge is particularly evident in oil and gas production systems, where pressure, temperature, fluid composition, and flow characteristics vary continuously throughout production operations [4]. As a result, traditional trial-and-error approaches are often inadequate for selecting the most suitable inhibitor or determining its optimum dosage under dynamic field conditions [10]. These limitations have accelerated the application of Artificial Intelligence (AI) and Machine Learning (ML) in corrosion engineering because these technologies can analyse large, multidimensional datasets, identify complex nonlinear relationships, and generate accurate predictive models that are difficult to achieve using conventional statistical methods [26]. AI-driven models have demonstrated considerable potential for predicting corrosion rates, optimizing inhibitor dosage, selecting suitable inhibitor formulations, and supporting intelligent corrosion management strategies that enhance asset integrity while reducing chemical consumption and operating costs [10, 26].

3.5. SURFACE CHARACTERIZATION TECHNIQUES USED IN CORROSION AND CORROSION INHIBITOR STUDIES

Surface characterization techniques are a cornerstone of corrosion science, characterizing surface morphology and chemical composition, as well as microstructural changes that occur on metal surfaces through the processes of corrosion and inhibition. These analytical techniques provide researchers with the means to assess corrosion inhibition by analyzing surface damage, protective film formation, corrosion products and adsorption mechanisms at the micro- and nanoscale [1, 19]. Characteristics of surfaces by electron microscopy, spectroscopy and diffraction-based techniques are well-established means to supplement the conventional electrochemical measurements with a direct way to gather evidence towards the performance of inhibitors and corrosion mechanisms [27]. Moreover, the quantitative data produced by these approaches are primary parameters for artificial intelligence and machine learning models in corrosion forecasting, inhibitor optimization [33] and intelligent asset integrity management [34]. Table 3 shows an overview of major surface characterization techniques used in corrosion and corrosion inhibitor research, together with operating principles, applications, advantages and disadvantages, as well as relevance for corrosion research.

TABLE 3 Surface Characterization Techniques for Corrosion and Corrosion Inhibitor Evaluation

Technique	Principle	Information Obtained	Advantages	Limitations	Typical Applications
Scanning Electron Microscopy (SEM)	A focused electron beam scans the specimen surface to generate high-resolution images [1].	Surface morphology, corrosion pits, cracks, inhibitor film coverage, corrosion products and microstructural changes [19].	High spatial resolution; excellent depth of field; rapid imaging of corrosion damage [23].	Requires conductive samples or conductive coating; provides limited chemical information without EDS [1].	Evaluation of inhibitor films, pitting corrosion, coating degradation, erosion-corrosion and fracture surfaces.

Energy Dispersive X-ray Spectroscopy (EDS/EDX)	Detects characteristic X-rays emitted from the sample during SEM analysis to determine elemental composition [19].	Qualitative and semi-quantitative elemental composition of corrosion products and inhibitor films [1].	Rapid elemental analysis; easily combined with SEM imaging [23]	Limited sensitivity for light elements; lower accuracy than XPS for surface chemistry [19].	Identification of corrosion products, elemental mapping and inhibitor adsorption studies.
Atomic Force Microscopy (AFM)	A sharp probe scans the surface to measure nanoscale topography through interatomic forces [1].	Surface roughness, film thickness, nanoscale morphology and inhibitor adsorption characteristics [27]	Extremely high vertical resolution; does not require conductive samples [19].	Small scanning area; relatively slow analysis [1].	Surface roughness measurement, adsorption studies and thin-film characterization.
X-ray Photoelectron Spectroscopy (XPS)	Measures the kinetic energy of emitted photoelectrons after X-ray irradiation to determine surface chemistry [27]	Chemical composition, oxidation states, bonding environment and inhibitor-metal interactions [12]	Highly surface-sensitive; provides detailed chemical state information [1].	Expensive instrumentation; requires ultra-high vacuum conditions [19].	Investigation of inhibitor adsorption mechanisms, passive films and corrosion products.
Fourier Transform Infrared Spectroscopy (FTIR)	Measures infrared absorption associated with molecular vibrations [27]	Functional groups present in inhibitor molecules and corrosion products; adsorption mechanisms [28]	Rapid, non-destructive and suitable for organic compounds [31]	Limited sensitivity for very thin surface films; overlapping absorption bands may complicate interpretation [27]	Identification of inhibitor functional groups and adsorption behaviour.
Raman Spectroscopy	Detects inelastic scattering of monochromatic light to identify molecular structures [19].	Chemical composition of corrosion products, oxides and adsorbed inhibitor species [1].	Minimal sample preparation; complementary to FTIR; high chemical specificity [23]	Fluorescence interference may reduce signal quality [1].	Characterization of corrosion scales, passive films and inhibitor adsorption.
X-ray Diffraction (XRD)	Uses diffraction of X-rays by crystal lattices to identify crystalline phases [23]	Crystal structure and phase identification of corrosion products and protective oxide films [19].	Accurate identification of crystalline compounds [1].	Cannot effectively detect amorphous materials; requires sufficient sample quantity [23]	Identification of corrosion scales, oxides and corrosion products.
Optical Microscopy (OM)	Uses visible light and optical lenses to magnify specimen surfaces [1].	General corrosion morphology, pit distribution, crack initiation and surface defects [19].	Simple, inexpensive and rapid [23]	Lower resolution than SEM or AFM [1].	Preliminary surface examination and metallographic analysis.
Contact Angle Measurement	Measures the angle formed between a liquid droplet	Surface wettability, hydrophobicity and effectiveness	Simple, rapid and non-destructive [12]	Sensitive to surface contamination and preparation	Evaluation of hydrophobic coatings and inhibitor-treated

	and the solid surface [27]	of protective inhibitor films [12]		procedures [27]	surfaces.
Confocal Laser Scanning Microscopy (CLSM)	Uses laser scanning and optical sectioning to produce three-dimensional surface images [19].	Three-dimensional pit depth, surface roughness and corrosion morphology [1].	Non-contact measurement; quantitative 3D analysis [23]	Higher equipment cost than conventional optical microscopy [19].	Quantification of pitting corrosion and coating degradation.

3.6. CURRENT CHALLENGES IN CONVENTIONAL CORROSION INHIBITOR APPLICATION

Despite decades of successful industrial application, several limitations continue to affect conventional corrosion inhibitor programs. The first is that inhibition selection is frequently based on the results of laboratory experiments which may not at all resemble real-world field conditions. Laboratory tests are usually conducted on simplified fluid compositions in controlled environments, while field systems undergo constant fluctuations in pressures, temperatures, flow regimes and fluid chemistries [9]. The second reason is that the optimal inhibitor dosage usually needs to be determined by field tests, which leads to a higher consumption of chemicals and operational costs. If you underdose, you can cause corrosion to the facilities, and if you overdose, it causes unnecessary operational costs and possibly introduces environmental or process compatibility issues. Third, corrosion monitoring data are usually taken from different sources (e.g., corrosion coupons, electrical resistance probes, linear polarization resistance measurements, fluid analyses and inspection reports). However, merging these heterogeneous data sources utilizing traditional analytical approaches poses a challenge and often causes them to be delayed in decision-making [35]. Fourth, environmental pressures have led to demand for eco-friendly inhibitor formulations that do not perform worse than conventional synthetic chemicals. Identifying such formulations through experimental screening alone is labor-intensive, time-consuming, and expensive [36, 37]. Finally, modern oil and gas facilities generate vast quantities of operational data from sensors, distributed control systems, laboratory databases, and inspection records. Traditional corrosion management methods cannot fully exploit these data to improve inhibitor selection and performance optimization.

These limitations have driven increasing interest in artificial intelligence, which offers advanced data analytics, predictive modeling, optimization algorithms, and intelligent decision-support systems capable of transforming corrosion inhibitor management [9, 35]. AI techniques can integrate laboratory results, field measurements, process variables, and historical operating data to recommend optimal inhibitor formulations and injection strategies with greater speed and accuracy than conventional approaches [9, 36].

4. ARTIFICIAL INTELLIGENCE TECHNIQUES IN CORROSION INHIBITION ENGINEERING IN OIL AND GAS

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly being investigated as data-driven approaches for improving the selection, performance prediction, optimization, and development of corrosion inhibitors [9, 26, 38]. Corrosion inhibition in oil and gas systems is inherently complex because inhibitor performance is affected by interacting variables such as inhibitor concentration and molecular structure, temperature, pressure, pH, water chemistry, CO₂ and H₂S concentrations, flow conditions, metallurgy, exposure time, and the composition of the hydrocarbon and aqueous phases [9, 10, 38]. These interactions can produce nonlinear relationships that are difficult to represent using conventional empirical models. Machine-learning approaches can identify such relationships from experimental and operational datasets and subsequently provide predictions of corrosion rate, inhibition efficiency, inhibitor performance, or suitable treatment conditions [9, 26, 38].

The application of AI to corrosion inhibition can be considered at several stages of the inhibitor-management process (FIGURE 3). These include predicting corrosion rate under inhibitor-treated conditions, estimating inhibition efficiency, identifying the influence of operating and treatment variables, optimizing inhibitor concentration and dosing schedules, screening potential inhibitor molecules, and integrating laboratory and field measurements for corrosion-management decisions. Hughes *et al.* [9] emphasized that the development of reliable ML models for corrosion inhibition depends strongly on the availability of sufficiently large and diverse inhibitor-performance datasets. More recently, Toor [26] emphasized the increasing application of AI and ML to inhibitor design, performance prediction, adsorption behaviour, and integration with electrochemical measurements. TABLE 4 gives a summary of recent studies on artificial intelligence-based corrosion prediction and corrosion inhibitor development.

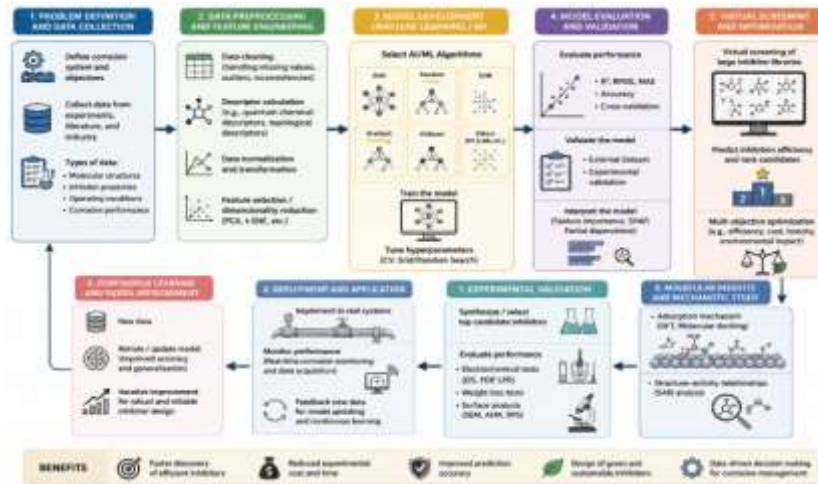


FIGURE 3 AI Workflow in Corrosion Inhibitor Design

TABLE 4 Summary of Recent Studies on Artificial Intelligence-Based Corrosion Prediction and Corrosion Inhibitor Development

AI Technique	Application	Key Findings	Limitations
Machine learning and computational modelling	Sustainable corrosion inhibitor design	Reported that AI-assisted molecular design and computational screening significantly accelerate the discovery of environmentally friendly corrosion inhibitors while reducing experimental cost and time	Limited industrial-scale validation and insufficient integration with real-time monitoring systems.
ANN, Random Forest, Support Vector Machine, Decision Tree	Corrosion prediction and materials engineering	Demonstrated that machine learning algorithms accurately model nonlinear corrosion behaviour and often outperform conventional empirical models in corrosion prediction	Performance strongly depends on the availability of high-quality datasets and appropriate feature selection.
Artificial Intelligence, Deep Learning, Machine Learning	Corrosion science and engineering	Concluded that AI significantly improves corrosion monitoring, predictive maintenance, materials selection and intelligent corrosion management	Highlighted challenges associated with explainability, model transferability and limited industrial deployment.
Digital Twin, Deep Learning, Industrial AI	Predictive maintenance in process industries	Demonstrated that digital twins integrated with AI improve equipment health monitoring, predictive maintenance and operational decision-making	High implementation cost and substantial sensor infrastructure required for deployment.
Computational chemistry and AI-assisted molecular design	Organic corrosion inhibitors	Reported that AI techniques facilitate rapid screening of inhibitor molecules, improving inhibitor efficiency and reducing experimental workload	Most applications remain at laboratory scale with limited field validation.
Artificial Neural Networks, Random Forest, Support Vector Machine, Deep Learning	Corrosion monitoring and prediction	Found that AI models frequently achieve prediction accuracies above 90% for corrosion rate estimation and equipment integrity assessment	Limited model interpretability and insufficient standardized benchmark datasets.
Artificial Intelligence, Computational Modelling, Molecular Simulation	Green corrosion inhibitor development	Demonstrated that AI combined with computational chemistry significantly accelerates the discovery and optimization of sustainable corrosion inhibitors while reducing laboratory experimentation.	AI-generated inhibitor candidates still require extensive experimental validation before industrial implementation

Source: Verma et al., [27]

4.1. MACHINE LEARNING (ML) FOR INHIBITOR EFFICIENCY PREDICTION

Out of all the branches, machine learning (ML) is the most frequently applied sub-group of AI in corrosion engineering because it can capture complex and nonlinear relationships directly from a large amount of data without needing mathematical equations of governing physical processes [39, 40]. In contrast to traditional modelling approaches which are based primarily on pre-defined physical equations and empirical correlations, machine learning algorithms automatically learn patterns from historical data and improve their predictive capacity as more training data becomes available [39]. This is a data-driven capability that really seems to lend itself well to machine learning and particularly corrosion prediction where environmental, operational and material factors interact in highly nonlinear ways [33, 34]. Machine learning techniques are generally classified into three broad categories: supervised learning, unsupervised learning (FIGURE 4) and reinforcement learning, each addressing different types of learning problems depending on the availability of labelled data and the desired learning objective [39, 40].

A very direct application for AI in the research of corrosion inhibitors is the prediction of inhibition efficiency. The target variable could be inhibition efficiency, while the predictor variables include inhibitor concentration, temperature, corrosive-medium composition, exposure time, material properties and molecular descriptors. ML models can then relate these variables to the inhibition efficiency determined experimentally. Recent studies showed that ML models can be trained to predict inhibitor activity using molecular and experimental features. Guo et al. AQSA — QSPR model for corrosion inhibitors. A QSAR model that tries to exemplify benzimidazole derivatives Sanders et al. This study shows an approach to represent molecular structure as numerical descriptors, which ML learns the mapping between chemical structure and kinase inhibitor performance.

Most recently, Alamiery and Shaker [29] evaluated the baseline of predictive capability using traditional ML versus state-of-the-art advanced ML for predicting corrosion-inhibitor efficiency across families of inhibitors. Their analysis showed how predictions of corrosion inhibitors have been applied to more and more conventional algorithms as well as advanced graph-based, deep-learning architectures. The authors also stressed the relevance of molecular structure, operational conditions and inhibitor concentration for predictive performance.

4.1.1. SUPERVISED LEARNING IN CORROSION ENGINEERING

Supervised learning involves training an algorithm using datasets in which the input variables and corresponding target responses are known. For corrosion-inhibition studies, input variables may include inhibitor concentration, temperature, pH, acid concentration, chloride concentration, exposure time, material characteristics, and other environmental parameters, while the target response may be corrosion rate or inhibition efficiency. Supervised-learning algorithms commonly applied to corrosion-inhibition problems include artificial neural networks (ANN), support vector machines (SVM), random forests (RF), decision trees, k-nearest neighbours (KNN), and gradient-boosting methods [26, 29]

Artificial neural networks are particularly useful for modelling nonlinear relationships between inhibitor-treatment variables and corrosion responses. Their application can enable the prediction of inhibition efficiency or corrosion rate at combinations of operating conditions that have not been directly evaluated experimentally. Alamiery and Shaker [29] reviewed applications of ANN and other ML algorithms for predicting corrosion-inhibitor efficiency and demonstrated the increasing use of molecular descriptors, operational variables, and inhibitor concentration as model inputs. However, ANN models can be sensitive to dataset size, data quality, network architecture, and overfitting, and their predictions require independent validation before being applied to field inhibitor-management decisions.

Random forest models provide another useful supervised-learning approach because they can represent nonlinear relationships and interactions between multiple corrosion and inhibitor variables [26, 13]. In addition, RF models can provide measures of variable importance that may help identify parameters contributing strongly to corrosion or inhibitor performance [10, 26]. SVM models can also be applied to corrosion-inhibition prediction, particularly when datasets are relatively small and nonlinear relationships are present [26, 13]. Recent reviews indicate that conventional algorithms such as ANN, RF, SVM, and KNN continue to be important approaches for corrosion-inhibitor prediction, although their relative performance depends on the dataset, response variable, descriptor selection, and validation procedure [10, 26, 29, 13]. An important application of supervised learning in oil and gas corrosion inhibition is the prediction of time-dependent corrosion behaviour under inhibitor treatment. Aghaaminiha *et al.* [42] developed machine-learning models for predicting corrosion-rate profiles of carbon steel in the presence of corrosion inhibitors and reported that the predicted corrosion response was influenced by environmental severity and inhibitor dose schedules. Such approaches are particularly relevant to oil and gas pipelines because inhibitor effectiveness may change with exposure time, treatment frequency, and changing operating conditions rather than remaining constant throughout the operating period.

4.1.2. UNSUPERVISED LEARNING IN CORROSION ENGINEERING

Unsupervised learning is applied when predefined target variables are unavailable, and the objective is to identify patterns, clusters, relationships, or underlying structures within a dataset [13, 43]. Principal component analysis (PCA) and clustering

techniques such as K-means can be used to analyse corrosion and inhibitor-treatment datasets containing multiple environmental and operational variables. In oil and gas corrosion management, these methods can potentially identify groups of production conditions with similar corrosion characteristics and thereby assist in differentiating inhibitor-treatment requirements [13, 44]. For example, production systems may be grouped according to similarities in temperature, pressure, water chemistry, CO₂ or H₂S concentration, water cut, flow conditions, and historical corrosion behaviour. Such clustering could help identify operating regimes in which a particular inhibitor formulation or dosage strategy is more appropriate. However, statistical groupings should be interpreted using corrosion-engineering knowledge because clustering identifies similarities in the data but does not independently establish the underlying corrosion or inhibition mechanism [38].

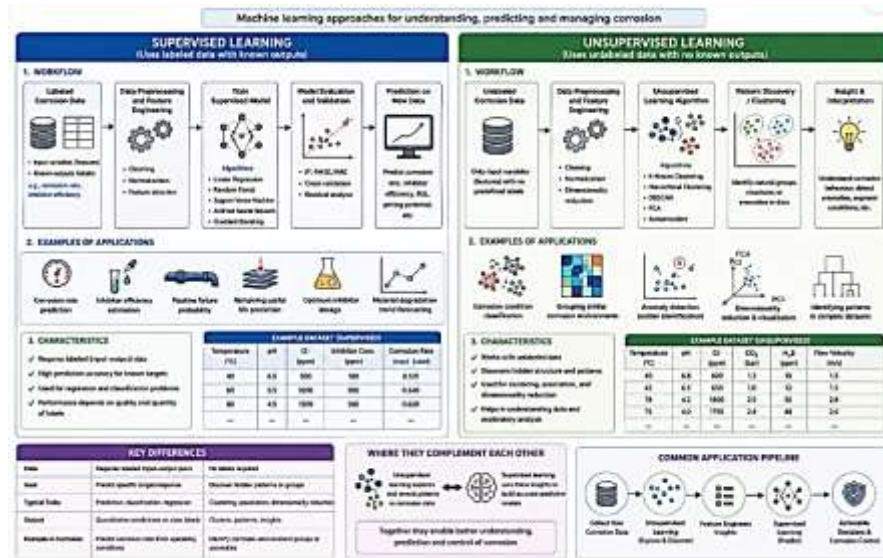


FIGURE 4 Supervised and Unsupervised Learning in Corrosion

4.2. ARTIFICIAL NEURAL NETWORKS (ANNs)

Artificial Neural Networks (ANNs) are among the earliest and most widely adopted artificial intelligence techniques in corrosion science and engineering due to their exceptional ability to model highly nonlinear and complex relationships among multiple variables [39, 40]. The study and construction of ANNs is related to that of biological neurons, in that an ANN is made up of interconnected processing elements, also called artificial neurons; these are organized into three groups: where input data is received, one or more hidden layers and the output layer, which produces an output signal similar to neuron firing. These layers are connected to one another, and the information is represented through these connections as it flows from one neuron to the other, where each neuron processes weighted input signals and sends its output signal to the neurons in subsequent layers. These connection weights are refined iteratively through optimization algorithms (e.g., backpropagation and gradient descent) to reduce prediction errors, allowing the network to generalize better on unseen datasets [39, 40]. The ability of ANNs to learn complex nonlinear relationships without the need for explicit mathematical models has proven attractive in corrosion engineering since corrosion behaviour is determined by a multitude of factors transpiring through complicated interactions among environmental, operational and material variables [33]. As a result, ANNs have been widely used for corrosion rate prediction, estimation of the efficiency of corrosion inhibitors, modeling CO₂ corrosion [34], H₂S corrosion [45], material degradation and pipeline integrity assessment. These applications facilitate proactive condition-based maintenance programs, maximizing the effectiveness of corrosion mitigation strategies and enhancing asset reliability for industrial assets including oil and gas, marine, chemical processing and power generation. Theoretically, the ANNs can capture complex interactions and nonlinear dependencies among large numbers of input variables simultaneously, thus typically outperforming more conventional statistical techniques such as linear [34] and multiple regression models [35, 36]. ANN models, for instance, demonstrate excellent prediction accuracy (several above 95% under well-trained conditions) of corrosion rate from process variables including temperature, pH, dissolved oxygen (conc.), chloride (conc.), inhibitor dosage, salinity, carbon dioxide partial pressure, hydrogen sulphide concentration (conc), flow velocity and exposure time within that chemical system as inputs [33] · E1425J Wiley et al. This degree of predictive accuracy has considerably improved the reliability of corrosion forecasting and aided in more efficient decision making in corrosion monitoring and asset integrity management.

However, ANNs have often been considered black-box models because the decision-making process is not readily interpretable by engineers and domain experts, even when inferred from available training datasets [39]. In contrast to the traditional mechanistic or statistical models, which provide explicit relationships between variables, ANN predictions are provided as a result of very complicated combinations that occur at hidden-layer computations, and thus it is hard to ascertain individual input parameter contributions. Due to limited interpretability, these ML systems are not as widely accepted in engineering applications that require transparent and explainable decisions where safety-critical reliability is crucial. In this

regard, the recent advancements in Explainable Artificial Intelligence (XAI) techniques such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME) and feature importance analysis can enhance model transparency by quantifying which variables have a strong influence on ANN predictions [33, 34]. Such developments have raised the level of trust around AI-enabled corrosion forecasting models and are anticipated to speed up their deployment in industrial corrosion monitoring as well as predictive maintenance systems. Figure 5 provides the ANN architecture for corrosion forecasting.

4.3. DEEP LEARNING (DL)

Deep learning (DL) is an advanced branch of machine learning that employs multilayer neural networks to automatically extract complex features from large and heterogeneous datasets. Unlike conventional artificial neural networks, deep learning models require minimal manual feature engineering and are particularly effective when trained using large volumes of laboratory, imaging, and operational data [2, 46]. DL extracts high-level features directly from high-dimensional, complex datasets. In corrosion informatics, recurrent neural networks (RNNs) and long short-term memory (LSTM) models are particularly effective for analyzing sequential telemetry, capturing temporal dependencies within real-time sensor streams and process variables. Simultaneously, work by Khalaf *et al.* [47] demonstrated that convolutional neural networks (CNNs) excel at processing surface image data, enabling automated feature extraction from laboratory microscopic evaluations and field non-destructive testing (NDT) inspections.

When applied to chemical treating workflows, deep learning algorithms synthesize historical chemical injection rates, fluid chemistry, and live metal-loss data to predict dynamic shifts in inhibition efficiency. However, a major bottleneck hindering widespread field adoption is the heavy data requirement of DL architectures compared to traditional statistical methods [9]. In corrosion science, experimental datasets remain notoriously small, fragmented, and condition-specific, presenting significant overfitting risks when training deep neural networks on limited field or bench-scale data [48].

4.4. SUPPORT VECTOR MACHINES (SVM)

Support Vector Machines (SVMs) are supervised machine learning algorithms widely used for classification and regression problems, particularly where datasets are relatively small but contain numerous variables. Their ability to model nonlinear relationships while maintaining good generalisation makes them well suited to laboratory corrosion studies, where generating experimental data is often expensive and time-consuming [10]. In corrosion engineering, SVMs have been applied to predict corrosion inhibitor efficiency, estimate electrochemical parameters, classify corrosion severity, and optimise inhibitor formulations. Although deep learning models generally outperform SVMs when very large datasets are available, SVMs remain attractive because of their robustness, lower computational requirements, and reduced susceptibility to overfitting [26].

4.5. RANDOM FOREST AND ENSEMBLE LEARNING

Random forest is an ensemble machine learning algorithm that combines the output from multiple decision trees to give a more accurate and stable prediction. The algorithm is particularly suited for noisy industrial datasets [2] since it reduces variance and minimises overfitting due to the overall prediction being an aggregation of predictions from many independent trees. In corrosion management, Random Forest models have been used to examine which of the key operational variables driving corrosion rates and inhibitor performance could improve the prediction of corrosion risk and support decision making [10]. Other ensemble methods, such as Gradient Boosting and Extreme Gradient Boosting (XGBoost), also proved to have good predictive performance [26].

4.6. FUZZY LOGIC SYSTEMS

Corrosion management often contains uncertainty due to missing measurements, changing operating conditions and professional assessments. These uncertainties can be well handled employing fuzzy logic: Variables are represented not as precise numerical values but rather in linguistic terms (e.g., as low, medium, high or critical). Fuzzy inference systems have been applied in all areas of corrosion engineering, including: corrosion risk modelling, intelligent inhibitor selection, maintenance prioritisation and, more recently, pipeline integrity assessment [2]. More recently, hybrid neuro-fuzzy systems [9], which combine the learning capability of neural networks with the interpretability of fuzzy logic, have produced more dependable and transparent decision-support systems regarding corrosion management [10].

4.7. GENETIC ALGORITHMS (GA)

Genetic algorithms (GAs) are heuristic methods that have found wide applications as intuitively inspired optimisation techniques. In the field of corrosion engineering, GAs have been applied in a wide range of problems, including but not limited to the optimisation of dosage for chemical inhibitors [25], molecular designs and formulations [24], and calculation of injection locations and conditions [26]. Traditionally employed optimising methods are local and execute local gradient-descent searches, while GAs do not need any gradient information and make global searches throughout the search range of the system [2]; as such, they can be used for systems in corrosion processes that experience multiple interactions within a regime of pressure, temperature, fluid chemistry, and inhibitor concentration.

4.8. REINFORCEMENT LEARNING (RL)

Reinforcement Learning (RL) is a new paradigm of AI in which an agent learns what actions to take in order to maximize its reward by running episodes or simulations in the environment where it has to operate. RL differs because, in addition to leveraging historical datasets, it continually receives feedback and uses that information to improve decision-making [49] and, as such, is especially attractive for applications with dynamic industrial systems. RL has demonstrated great promise in corrosion engineering, enabling autonomous control of iterative inhibitor injection [16], adaptive corrosion management [24], predictive maintenance scheduling, and digital twin-based process optimisation [26]. Improvements in online corrosion technologies will create a constant need to perform such monitoring using real-time data, advancing autonomous asset integrity operations with regard to the response made by reinforcement learning (RL).

4.9. HYBRID ARTIFICIAL INTELLIGENCE MODELS

In recent years, hybrid systems research has received more and more attention, as scientists combine multiple complementary algorithms to increase the accuracy and robustness of the prediction tasks while maintaining interpretability. They are represented in the form of hybridised networks such as artificial neural network–genetic algorithm (ANN–GA), CNN–LSTM, SVM–GA, random forest– XGBoost, and neuro-fuzzy systems that play a significant role to optimise and entropy balance between the strengths of individual techniques and their various limitations [10]. Physics-Informed Machine Learning (PIML), in many applications, existing knowledge and laws from electrochemical fundamentals, reaction kinetics, mass transfer, and thermodynamic constraints can be incorporated into machine learning algorithms. PIML encapsulates prior knowledge by embedding established corrosion science within AI models to reduce data dependence and increase prediction reliability, thus making it particularly powerful for more complex corrosion environments where experimental datasets are difficult to generate [11, 26].

4.10. AI FOR INHIBITOR DOSAGE AND TREATMENT OPTIMIZATION

Prediction of inhibitor performance does not necessarily identify the optimum treatment concentration, because predictive models estimate system responses whereas optimization seeks treatment conditions that satisfy specified performance objectives and constraints [26, 13]. In oil and gas production systems, the objective is generally to achieve adequate corrosion protection while avoiding unnecessary chemical consumption and associated operating and environmental costs [6, 7]. This enables AI-based optimization to be combined with predictive models identifying inhibitor concentrations and treatment conditions satisfying a user-defined corrosion-control objective subject to relevant operating constraints [26, 13, 7].

Evolutionary optimization algorithms Genetic Algorithm (GA), Particle Swarm Optimization (PSO), integrated with Artificial Neural Networks (ANN), response-surface models or other predictive algorithms, remain effective for searching the appropriate combination of inhibitor concentration and operating conditions [56–58]. As an example, the predictive model could estimate corrosion rate based on a function of inhibitor concentration, temperature, pH and other environmental determinants, with a search algorithm to identify treatment conditions that keep corrosion below a desired target [51, 53]. The evolutionary optimization approaches for estimating corrosion-inhibitor dosages and integration with decision-making concerning treatment use have been demonstrated recently [53, 54]. Thus, this prediction–optimization framework may provide a route towards transition from static inhibitor-treatment practices to personalized dosing approaches [53].

The importance of optimizing inhibitor dosage is also demonstrated by studies of time-dependent inhibitor performance. Aghaaminiha *et al.* [42] showed that corrosion-rate profiles are affected by inhibitor dose schedules and environmental severity, highlighting the importance of considering both inhibitor concentration and treatment history rather than evaluating inhibitor effectiveness solely at a single experimental condition.

4.11. QSAR, MOLECULAR DESCRIPTORS AND AI-ASSISTED INHIBITOR DESIGN

Quantitative structure–activity relationship (QSAR) modelling is a critical bridge between AI and the molecular design of corrosion inhibitors. [27, 38] QSAR approaches create a mathematical model that relates molecular descriptors to empirical inhibition performance, enabling the prediction of potentially active compounds without ever having tested them in vitro. [9, 27]. Molecular descriptors might be molecular weight, surface area, electronegativity, dipole moment, polarizability of the molecule frontier molecular orbital energies and energy gap or many other topological or physicochemical entities [10], [27], [38].

Guo *et al.* QSAR modelling of benzimidazoles using machine learning techniques was performed to predict the efficacy of inhibition with multiple descriptors, as reported by [41]. They thus demonstrate how descriptor-based ML approaches can help to lessen reliance on large-scale experimental screening during inhibitor development. Baskin *et al.* It has been pointed out [48] that organic corrosion-inhibition datasets are usually small, and that inhibition performance correlates with adsorption mechanism and multiple experimental parameters. Such characteristics pose specific challenges for the development of robust chemoinformatics and ML models. Hence, descriptor selection, appropriate cross-validation, and uncertainty quantification should be incorporated together into model development, and predictions of inhibitor performance need to be experimentally verified.

AI can also be combined with computational chemistry methods, e.g., density functional theory (DFT) and molecular dynamics (MD). DFT yields electronic and molecular descriptors for the interactions between inhibitor reactivity and adsorption, whereas MD simulations reveal information on how well inhibitor molecules interact with metal surfaces. The computational descriptors are then applied as ML model inputs for inhibition performance predictions and candidate molecule screening. Such integration provides a potential route toward rational inhibitor design in which computational screening precedes synthesis and laboratory testing [26, 38].

4.12. PHYSICS-INFORMED AND EXPLAINABLE AI FOR CORROSION INHIBITION

Purely data-driven models can identify statistical relationships without necessarily ensuring consistency with established corrosion mechanisms [9, 26]. Physics-informed machine learning (PIML) provides an alternative approach in which known physical relationships or constraints are incorporated into the modelling process [26, 55]. For corrosion inhibition, relevant physical knowledge may include electrochemical kinetics, inhibitor adsorption, mass transfer, diffusion, thermodynamic behaviour, and transport phenomena [55, 56]. Incorporating such knowledge may improve the physical consistency and generalizability of AI predictions, particularly where experimental datasets are limited [26, 55].

Explainable artificial intelligence (XAI) has also been important for corrosion-inhibitor applications, as knowledge about the contributing factors of model predictions can support the evaluation and safe use of AI-based recommendations in engineering practice [26, 13]. Methods such as feature-importance analysis, partial-dependence methods, SHAP-based explanations and related techniques can facilitate causal interpretation because they identify which variables have the strongest contribution to predicted corrosion rates or inhibitor performance [13, 57, 58]. One such use case is SHAP analysis, which can estimate the contribution an individual input feature makes to a particular model prediction and can thus help to understand the reasons behind any corrosion or inhibition performance [57, 58]. Explainability is particularly relevant where AI recommendations may influence inhibitor dosage, asset-integrity management, or other safety-related operational decisions, although interpretability should be considered alongside model validation, uncertainty assessment, and physical consistency [26, 13].

4.13. SELECTION OF AI TECHNIQUES FOR CORROSION-INHIBITOR MANAGEMENT

No single AI technique is universally suitable for all corrosion-inhibition applications. The selection of an algorithm should depend on the modelling objective, dataset size and quality, variable types, temporal characteristics, required level of interpretability, and the consequences of prediction errors [10, 26, 38, 47]. Supervised-learning models are suitable for predicting measurable responses such as corrosion rate and inhibition efficiency [10, 26], whereas unsupervised methods can assist in identifying patterns and groups of similar corrosion environments [38, 47]. Optimization algorithms can be coupled with predictive models to determine suitable inhibitor concentrations and operating conditions [26, 38], while QSAR and molecular machine-learning approaches can support inhibitor discovery, molecular screening, and prediction of inhibition performance [26, 10]. Deep-learning methods may be particularly useful when large and complex datasets, including time-series, image, or molecular-structure data, are available [26, 38], whereas fuzzy, hybrid, reinforcement-learning, and physics-informed approaches may provide additional capabilities for decision support, adaptive control, and physically constrained corrosion-management applications [26, 38, 55].

For oil and gas applications, however, predictive performance alone should not determine algorithm selection. The reliability of an AI-based inhibitor-management system also depends on data representativeness and quality, experimental reproducibility, external validation, uncertainty quantification, model interpretability, and compatibility with established corrosion-management practices [43, 47, 50, 59]. Statistical performance metrics such as high R^2 or low prediction error do not necessarily guarantee physical validity, robustness, or transferability to real operating environments [43, 50]. Laboratory predictions should therefore be validated experimentally and, where possible, against field measurements before AI recommendations are used to modify inhibitor-treatment strategies [47, 50, 59].

4.14. ADVANTAGES OF AI OVER CONVENTIONAL CORROSION MODELING

The increasing adoption of AI in corrosion engineering is driven by several advantages over traditional empirical and mechanistic models (TABLE 5).

TABLE 5 Comparison between Conventional Corrosion Modeling and AI Approaches

Feature	Conventional Methods	Artificial Intelligence
Model development	Empirical equations	Data-driven learning
Nonlinear relationships	Limited capability	Excellent capability
Large datasets	Difficult to analyze	Easily processed
Real-time prediction	Limited	Potentially effective with suitable data and infrastructure
Continuous improvement	Requires manual updating	Can be updated with new data
Optimization	Trial-and-error	Can support constrained optimization
Computational efficiency	Moderate	High after training
Decision support	Limited	Intelligent recommendations
Adaptability	Low	High

The combination of artificial intelligence (AI) with laboratory experimentation, field study, computational modelling and real-time corrosion monitoring helps to improve corrosion inhibitor management in oil and gas. AI allows for the identification of complex patterns from large and perpetually generated datasets, thus enabling increased accuracy in corrosion prediction as well as assisting informed decision-making and solution creation under varying operating conditions [2]. This allows for an intelligent selection of corrosion inhibitors, optimization of the dosage of inhibitor, real-time assessment of the risk of corrosion and even development of autonomous corrosion management systems that improve asset integrity while reducing maintenance costs and chemical consumption [10, 26]. In addition, the combination of AI with digital twins, IIoT sensors, and cloud-based analytics is enabling proactive and adaptive sonar-prediction corrosion management to help operators proactively adapt oil and gas operations for operational safety, reliability and sustainability [9, 11].

5. AI-ENHANCED CORROSION INHIBITOR APPLICATIONS IN OIL AND GAS FACILITIES

Artificial intelligence (AI) and machine learning (ML) are increasingly being investigated as tools for corrosion-inhibitor management in oil and gas facilities. Conventional inhibitor programs rely on laboratory qualification, corrosion monitoring, field experience, and established chemical-treatment practices. AI can complement these approaches by modelling nonlinear relationships among operating conditions, fluid chemistry, inhibitor characteristics, and corrosion response. Recent studies have demonstrated applications in time-dependent corrosion prediction, inhibitor screening, dosage optimization, and data integration; however, most evidence remains based on laboratory, pilot, or bounded datasets rather than fully autonomous field deployment [9, 11, 26, 42, 53].

5.1. AI-ASSISTED CORROSION-RATE PREDICTION UNDER INHIBITOR TREATMENT

Reliable corrosion-rate forecasting provides the baseline metric for evaluating whether an active chemical injection program maintains sufficient surface protection [33, 60]. Empirical correlations and thermodynamic models provide baseline estimates, but are less reliable when various operational variables change concurrently [43, 33]. Instead, machine learning algorithms overcome these limitations by directly training on the high-dimensional data across temperature, pH, acid gas loading, hydrodynamic shear and inhibitor residual concentrations in those datasets [43, 47, 60].

In a seminal empirical study, Aghaaminiha et al. [42] also conducted supervised machine-learning explorations to predict time-dependent corrosion rates of carbon steel in conjunction with varying inhibitor dosing schedules. They found that though immediate corrosion-rate time profiles rely on injection frequency, long-term steady-state rates are mainly controlled by environmental severity. One successful architecture, specifically Random Forest regressors, captured the transient kinetics of film formation and decay accurately to predict full corrosion-rate profiles as a function of fluid environment. This is important for field management: operators can use ensemble models to either continuously check whether film decay is occurring, or chemical re-injection is required instead of single-point-in-time snapshot measurements.

5.2. AI-ASSISTED CORROSION INHIBITOR SELECTION

The choice of the best corrosion inhibitor involves more than only the finding of the formulation with the maximal static inhibition efficiency (IE) in autoclave test. The successful candidate will need to ensure thermal stability during field operations, minimize emulsification, avoid downstream catalyst poisoning and meet regional eco-toxicity regulations. Instead of adopting a completely experimental high-throughput shotgun approach, however, AI architectures scan historical field logs and large experimental libraries to provide the contextual classification of chemical formulations based on past successes. As reviewed by Riyaz et al. [10], modern machine learning frameworks quantitatively assess both molecular descriptors and operational parameters in order to predict candidate performance over targeted production envelopes. Both classical algorithms like Support Vector Machines (SVM) and Random Forests and more sophisticated ones like Graph Neural Networks (GNNs) map structural moieties to inhibition kinetics. In the end, instead of simply finding a general "high-performance" inhibitor, we are engineering a formulation that is specific to the condition on how it can be identified within the unique metallurgical/hydrodynamic chemical limits of a facility.

5.3. AI-BASED OPTIMIZATION OF CORROSION INHIBITOR DOSAGE

Optimizing chemical injection rates is an important potential application of AI in corrosion-management systems. The aim is to provide just adequate corrosion protection while not overconsuming chemicals and thereby potentially creating an unnecessary environmental burden and process-compatibility issues. Sanni et al. [61] applied ANN and ANFIS modeling to predict inhibitor performance under simulated acidizing conditions, Jayaweera et al. As demonstrated by [53], it is not sufficient to have a predictive model with high accuracy alone for opting an optimal dosage of the inhibitors reliably.

The recommended dosing of AI-based inhibitors should preferably be confined within prescribed engineering boundaries. Keep validating model predictions with independent corrosion-monitoring and chemical-treatment data, including LPR measurements, ER probes, and residual inhibitor analysis. Jayaweera et al. [53] state that reliable optimization of inhibitor dosage requires that both prediction accuracy and reasonable representation of the relationship between inhibitor concentration and corrosion rate are met. Similarly, Khalaf et al. [47] stressed the significance of data quality, model validation and

interaction of AI with traditional corrosion-monitoring strategies. We suggest that AI recommendations stay within known process and operating limits and undergo review prior to the implementation of significant changes in treatment.

5.4. AI-DRIVEN DISCOVERY AND DESIGN OF CORROSION INHIBITORS

The chemical search space for organic corrosion inhibitors is large, making experimental synthesis and electrochemical evaluation resource-intensive. Computational workflows combining quantitative structure–activity relationship (QSAR) models with quantum-chemical and molecular-simulation descriptors can reduce the number of candidates requiring experimental evaluation [11, 26, 36, 38]. Özkan *et al.* [11] developed an electrochemical library of approximately 80 inhibitor candidates and demonstrated the value of combining time-dependent electrochemical measurements with molecular descriptors for ML-assisted inhibitor discovery. Such computational screening should nevertheless be followed by experimental qualification before field application.

5.5. AI FOR GREEN CORROSION INHIBITOR DEVELOPMENT

The transition toward environmentally benign "green" inhibitors sourced from plant extracts, amino acids, and biopolymers presents unique modeling challenges. In contrast to synthetic molecules, which usually have one fixed chemical structure, natural extracts are composed of mixtures of plant phytochemicals, and their active concentrations vary with geographical origin, harvest season or extraction methodology.

To combat this compositional uncertainty, AI-based predictions map multi-component chromatographic profiles against experimentally determined inhibition performance. As discussed by Özkan *et al.* Dua *et al.* (2018), Pappas *et al.* [11] and Toor [26], machine learning models can identify active phytochemical constituents that synergistically interact to determine anti-oxidative efficacy, allowing drug developers to formulate standardized efficient green additives as well as a sustainable source of such green drugs. However, field implementation requires rigorous verification: candidate green formulations must undergo experimental testing to confirm high-temperature thermal stability, low partitioning into the hydrocarbon phase, and complete compatibility with co-injected production chemicals.

5.6. AI-INTEGRATED REAL-TIME CORROSION MONITORING AND INHIBITOR MANAGEMENT

Modern production and pipeline facilities can generate high-frequency integrity data from electrical-resistance (ER) probes, linear-polarization-resistance (LPR) sensors, ultrasonic thickness (UT) measurements, localized-corrosion monitoring systems, and process or fluid analyzers (TABLE 6) [47, 62, 63]. These heterogeneous data streams can provide information on corrosion rate, metal loss, fluid chemistry, and changing operating conditions, although individual sensor technologies have different measurement capabilities and limitations [62, 63]. AI and machine-learning algorithms can integrate and analyze such multidimensional data to identify temporal patterns, detect changes in corrosion behaviour, and support forecasting of metal-loss trends [47, 64, 65].

TABLE 6 Monitoring Sensors for High-Frequency Integrity Data

Monitoring Technology	Measured Parameter	Primary AI Data Integration Role
Electrical Resistance (ER)	Cumulative metal loss	Time-series forecasting of long-term wall thinning
Linear Polarization (LPR)	Instantaneous corrosion rate	Real-time feedback for dynamic chemical dose adjustment
Electrochemical Noise (EN)	Localized pitting events	Early anomaly detection and pitting risk classification
Ultrasonic Thickness (UT)	Direct wall thickness	Model recalibration and inspection interval optimization

Operational shifts such as changes in water cut, acid-gas loading, temperature, flow conditions, or fluid chemistry can alter corrosion and inhibitor performance. Time-series AI models may help identify emerging changes in corrosion behaviour from high-frequency monitoring data. However, real-time prediction should be distinguished from autonomous chemical injection: AI systems should initially function as decision-support layers that integrate monitoring evidence and alert corrosion or production-chemistry personnel to conditions requiring investigation.

5.7. AI-SUPPORTED PREDICTIVE MAINTENANCE AND CORROSION RISK MANAGEMENT

Predictive maintenance can extend AI-based corrosion management into the broader asset-integrity framework. Machine-learning models that integrate corrosion predictions with inspection results, operating data and maintenance records constitute a tool to help identify pipeline sections needing further investigation [65]. In response to a finding of increased predicted corrosion risk, such actions could be checks on chemical-injection performance, Measured inhibitor residuals, Reviews of fluid chemistry and the execution of any appropriate non-destructive testing. AI should supplement established asset-integrity and engineering assessment activities, rather than substitute for them.

5.8. AI, INDUSTRIAL INTERNET OF THINGS, AND DIGITAL TWINS

The convergence of Industrial Internet of Things (IIoT) edge devices, cloud computing, and physics-informed machine learning (PIML) enables the creation of dynamic Corrosion Digital Twins. A digital twin maintains a continuous computational replica of a physical facility, ingesting real-time operational telemetry to simulate internal degradation. By

embedding electrochemistry and multiphase flow hydrodynamics directly into data-driven models, physics-guided digital twins evaluate "what-if" scenarios such as predicting how increasing production rates or altering fluid temperatures will impact chemical film coverage before physical adjustments are executed in the field.

5.9. TOWARD INTELLIGENT AND ADAPTIVE CORROSION-INHIBITOR MANAGEMENT

Integrating these computational tools establishes an end-to-end operational workflow for modern chemical treating. Rather than relying on static field protocols, intelligence is embedded across every phase of the inhibitor life cycle.

- **Environment Characterization: Process & Fluid Baseline.** Gather real-time and historical baseline data on fluid chemistry, partial pressures (CO_2 , H_2S), water cut, and hydrodynamic shear stress.
- **In Silico Screening & Selection: Computational Evaluation.** Apply QSAR models and DFT binding energy predictions to screen candidate molecules and select condition-specific chemical formulations.
- **Predictive Dosage Optimization: Algorithmic Tuning.** Use constrained optimization algorithms (PSO/ANFIS) to establish the minimum effective chemical injection rate required for target protection limits.
- **IIoT Field Telemetry & Digital Twin Monitoring: Real-Time Verification.** Continuously track film performance and metal loss via LPR/ER probes, ingesting live telemetry into a physics-informed digital twin.
- **Model Recalibration & Engineering Review: Human-in-the-Loop Feedback.** Validate model predictions against physical coupon weight-loss assays and chemical residual titrations, updating AI model parameters under human oversight. As emphasized by Özkan *et al.* [11] and Riyaz *et al.* [10], current industrial implementation favors this structured, human-in-the-loop framework over fully autonomous chemical injection, ensuring operational safety while maximizing integrity performance.

5.10. CRITICAL ASSESSMENT OF AI APPLICATIONS IN CORROSION-INHIBITOR MANAGEMENT

Published literature demonstrates useful predictive performance for several AI applications in corrosion science, but the level of technological maturity varies considerably. Laboratory-scale corrosion-rate prediction, QSAR screening, and offline optimization are relatively more developed, whereas adaptive online dosage control, autonomous IIoT-based chemical management, and reliable transfer between facilities remain emerging applications requiring substantial field validation [9, 11, 26, 53].

- **High Maturity (Laboratory Scale):** AI-driven corrosion rate prediction, QSAR molecular screening, and offline dosage optimization within bounded experimental datasets are well-developed and validated.
- **Low-to-Moderate Maturity (Field Scale):** Fully adaptive online dosage control, autonomous IIoT closed-loop chemical management, and cross-facility model transferability remain emerging concepts requiring extensive field trials.

The primary obstacle to field-scale deployment remains data heterogeneity and sparsity. Experimental corrosion datasets are frequently collected under disparate laboratory conditions, varying metal microstructures, and differing exposure durations [10]. Özkan *et al.* [11] proposed that establishing standardized, time-dependent electrochemical benchmark libraries is a vital prerequisite for building generalizable, field-ready AI models. Consequently, AI functions most effectively as an engineering decision-support engine augmenting the speed, consistency, and diagnostic depth available to asset integrity managers.

5.11. EVIDENCE MATURITY AND DEPLOYMENT READINESS

The evidence reviewed in this study suggests that AI applications in corrosion-inhibitor management can be considered along a progression from computational screening to laboratory validation, field decision support, and ultimately closed-loop control. QSAR and molecular ML are primarily useful for candidate prioritization; corrosion-rate models can support prediction within validated operating domains; and dosage-optimization models can support treatment decisions when sufficient monitoring and process data are available [11, 26, 36, 53].

The transition from prediction to operational control requires additional evidence. Laboratory performance does not by itself establish field suitability, and high statistical accuracy does not guarantee reliable extrapolation to unfamiliar inhibitor chemistries or operating conditions [9, 11, 53]. Accordingly, the most defensible near-term role for AI is as a human-in-the-loop decision-support layer that combines model predictions with corrosion monitoring, inhibitor-residual measurements, process data, and engineering constraints. Fully autonomous chemical control should be regarded as an emerging research direction requiring extensive field validation, uncertainty assessment, and safety assurance.

6. CHALLENGES, LIMITATIONS, AND FUTURE RESEARCH DIRECTIONS IN AI-BASED CORROSION INHIBITOR APPLICATIONS

Although artificial intelligence (AI) and machine learning (ML) have demonstrated potential for corrosion-inhibitor selection, inhibition-efficiency prediction, dosage optimization, inhibitor discovery, and treatment monitoring, their application remains subject to several limitations. The principal challenges are associated with the availability and quality of corrosion-inhibitor datasets, transferability of models between different inhibitor chemistries and operating environments, experimental validation, model interpretability, prediction uncertainty, and integration with practical inhibitor-treatment systems. Recent studies have

emphasized that the reliability of AI-based inhibitor models depends strongly on the quality, diversity, and consistency of the experimental data used for model development [10, 11, 26].

6.1. AVAILABILITY AND QUALITY OF CORROSION-INHIBITOR DATA

The availability of reliable experimental data remains one of the major limitations to the development of AI models for corrosion-inhibitor applications. Inhibitor datasets are often generated using different metals, electrolytes, temperatures, inhibitor concentrations, exposure times, experimental procedures, and corrosion-measurement techniques. Consequently, data generated from different studies may not be directly comparable.

Özkan *et al.* [11] demonstrated the importance of generating high-quality and time-dependent experimental data for ML-assisted inhibitor discovery. Their study combined electrochemical measurements with molecular descriptors and showed that experimental information such as pH and time-dependent electrochemical behaviour can provide important information for data-driven inhibitor modelling. Riyaz *et al.* [10] similarly identified data scarcity and heterogeneity as important challenges affecting the development and generalization of corrosion-inhibitor prediction models.

For oil and gas applications, inhibitor datasets should ideally include inhibitor identity and concentration, molecular descriptors, metallurgy, temperature, pressure, pH, water chemistry, CO₂ and H₂S concentrations, exposure time, flow conditions, corrosion rate, inhibition efficiency, and measurement method. Development of standardized and machine-readable corrosion-inhibitor databases would improve model training, comparison, reproducibility, and independent validation.

6.2. TRANSFERABILITY OF AI MODELS ACROSS INHIBITORS AND OPERATING CONDITIONS

The reliability of an AI model developed for corrosion inhibition can be strongly influenced by the specific inhibitor, metal, and experimental conditions used during model development. A model trained under one laboratory environment may therefore not necessarily provide reliable predictions when applied to a different inhibitor, material, or operating condition. This is because corrosion-inhibitor performance is governed by the complex interaction between inhibitor chemistry and the metal surface, as well as environmental and operating variables such as electrolyte composition, temperature, pressure, acid-gas concentration, flow conditions, and exposure time [20, 6]. Recent studies on machine-learning-based corrosion modelling have similarly highlighted the importance of representative and sufficiently diverse datasets for developing models that can generalize beyond the conditions used for training [9, 11]. Consequently, a model developed from a single corrosion system may have limited predictive capability when transferred to another system with different materials, inhibitor chemistry, or environmental conditions. Improving model generalizability therefore requires datasets that cover a sufficiently broad range of inhibitors, materials, and operating conditions, together with appropriate model validation using independent experimental data [10, 48]. This limitation is particularly important in oil and gas facilities, where corrosion environments vary considerably between production wells, flowlines, separators, pipelines, and processing equipment. An inhibitor that performs effectively in one environment may exhibit different behaviour when the water chemistry, temperature, metallurgy, or hydrocarbon composition changes. Riyaz *et al.* [10] emphasized the limited generalizability and transferability of ML models as important challenges in corrosion-inhibitor prediction. Future studies should therefore evaluate AI models using independent datasets obtained from different inhibitor formulations, materials, laboratories, and operating environments. Transfer learning, domain adaptation, and uncertainty-aware modelling may provide useful approaches for improving model transferability.

6.3. EXPERIMENTAL VALIDATION OF AI-PREDICTED INHIBITOR PERFORMANCE

Hence, using AI prediction can never supplant experimental qualification of corrosion inhibitors. However, a confirmation of inhibitor performance using laboratory techniques such as weight-loss measurements, potentiodynamic polarization, linear polarization resistance (LPR), electrochemical impedance spectroscopy (EIS) and surface characterization is still required. The significance of experimental validation is especially apparent in the context of AI-assisted inhibitor discovery. Özkan *et al.* An experimental framework with electrochemical measurements and molecular descriptors to generate a dataset suitable for ML-based inhibitor discovery has been demonstrated [11]. These types of methods underscore the importance that robust experimental data, rather than computational descriptors alone, are necessary for reliable AI models.

For oil and gas applications, a suitable development pathway should therefore involve computational screening followed by laboratory qualification and, where appropriate, field testing. AI predictions can reduce the number of candidates requiring extensive experimentation, but predicted inhibition efficiency should be treated as a basis for prioritization rather than definitive evidence of field performance [11].

6.4. EXPLAINABLE AI FOR INHIBITOR SELECTION AND DOSAGE OPTIMIZATION

The increasing use of complex ML algorithms creates a challenge concerning the interpretation of AI recommendations. For corrosion-inhibitor applications, engineers might be wondering why an AI model is predicting high inhibition efficiency for a particular compound favourably and recommending a specific inhibitor concentration [47]. Explainable AI (XAI) approaches, by their definition, can provide information about the variables that control the model predictions. For instance, feature-importance methods can determine which variables, such as inhibitor concentration, temperature, pH, acid-gas concentration or

molecular descriptors, have the highest impacts on predicted inhibition performance. This allows for better confidence and comparisons with established corrosion mechanisms when using AI-based recommendations. Hence, in future research, AI models should be evaluated not only on predictive accuracy but also interpretability. The ultimate goal should be to build models that cannot only predict corrosion rate or inhibition efficiency but also provide technically interpretable reasons for the prediction.

6.5. UNCERTAINTY AND RELIABILITY OF AI-BASED INHIBITOR RECOMMENDATIONS

Prediction accuracy alone is not sufficient to determine whether an AI model is reliable enough for operational decision-making. A model may perform well when tested on data that are similar to those used during training but become less reliable when it encounters unfamiliar inhibitor chemistries or operating conditions. This limitation is particularly important in corrosion-inhibitor dosage optimization because inhibitor performance is influenced by several interacting variables, and relationships learned from one corrosion environment may not necessarily remain valid under different conditions [9, 11]. For example, an AI model may identify a particular inhibitor concentration as optimal based on historical operating data, yet the actual field environment may change because of variations in water cut, temperature, pressure, fluid chemistry, production rate, flow conditions, or residual inhibitor concentration. Jayaweera *et al.* [53] demonstrated this challenge in data-driven inhibitor-dosage optimization, showing that high prediction accuracy alone does not guarantee that a model adequately captures the influence of inhibitor concentration on corrosion rate. They emphasized that the model must also demonstrate sufficient sensitivity to the inhibitor variables before it can be reliably used for dosage optimization. Therefore, AI-based inhibitor recommendations should be evaluated using independent and representative datasets and, where possible, validated under changing operating conditions before being applied to field-scale corrosion-management decisions.

Future AI systems for corrosion inhibitor management should therefore incorporate uncertainty quantification and mechanisms for detecting when operating conditions or inhibitor chemistries fall outside the model's applicability domain. This is important because predictions made for conditions that differ substantially from those represented in the training dataset may be less reliable. Recent studies on corrosion-inhibitor modelling have emphasized that models should be evaluated not only by their predictive accuracy, but also by their ability to recognize unfamiliar chemical and operating conditions and communicate the associated uncertainty [9, 48].

Where the predicted uncertainty is high, the AI system should not automatically increase or decrease the inhibitor dosage. Instead, the result should trigger additional laboratory testing, closer corrosion monitoring, or review by a corrosion engineer before any operational change is implemented. This approach would allow AI to function as a decision-support tool rather than an autonomous controller, particularly when predictions are made outside the conditions for which the model has been adequately validated. Such uncertainty-aware and experimentally validated approaches can improve the reliability and practical adoption of AI-based corrosion-management systems [11, 26].

6.6. INTEGRATION WITH CORROSION-INHIBITOR MONITORING AND DOSAGE CONTROL

Another important challenge is the integration of AI predictions with existing corrosion-inhibitor treatment and monitoring systems. In practical oil and gas facilities, inhibitor management relies on several complementary sources of information, including chemical-injection systems, corrosion coupons, electrical resistance (ER) and linear polarization resistance (LPR) probes, laboratory analyses, inhibitor-residual measurements, and process and production data. Corrosion coupons and ER probes, for example, are commonly used for monitoring internal corrosion in oil and gas production and processing systems, while LPR measurements can provide more frequent estimates of corrosion behaviour [67]. Jayaweera *et al.* [53] similarly demonstrated the potential for using routinely measured LPR corrosion-rate data together with water-quality and chemical-concentration data in data-driven approaches for corrosion-inhibitor dosage optimization.

AI can potentially integrate these different data streams to provide continuous or near-real-time estimates of corrosion behaviour, inhibitor effectiveness, and treatment requirements. However, reliable implementation depends strongly on the quality, consistency, and representativeness of the data supplied to the model. Appropriate sensor validation, consistent data acquisition, suitable sampling frequency, synchronization of measurements, and compatibility with existing process-control and chemical-injection infrastructure are therefore important considerations. Jayaweera *et al.* [53] showed that the choice and characteristics of input variables can substantially influence both the predictive performance of a corrosion model and its ability to capture the actual influence of inhibitor concentration. Their findings indicate that high prediction accuracy alone is not sufficient when the model does not adequately represent the effect of the inhibitor on corrosion behaviour.

A further consideration is that an observed increase in corrosion rate does not necessarily indicate insufficient inhibitor dosage. Corrosion behaviour can be affected by several interacting factors, including changes in water chemistry, flow conditions, temperature, corrosive species, material characteristics, and chemical concentrations. Consequently, interpreting a change in corrosion rate requires consideration of the wider operating and chemical environment rather than relying on a single monitoring variable. This is particularly important for AI-based dosage optimization because models can assign excessive

importance to variables that are strongly correlated with corrosion rate while failing to adequately capture the actual effect of inhibitor concentration [53].

Accordingly, AI-based inhibitor-management systems should incorporate multiple sources of information, including corrosion-rate measurements, inhibitor-residual concentration, water and fluid chemistry, temperature, pressure, flow conditions, injection performance, and relevant laboratory results. Combining these variables can provide a more comprehensive representation of the corrosion environment and reduce the risk of making dosage recommendations from corrosion-rate data alone. Jayaweera *et al.* [53] further suggested that combining mechanistic understanding with data-driven modelling may be necessary because corrosion involves several interacting reactions that cannot always be adequately represented by a purely data-driven model. Thus, AI is better positioned as a multivariable decision-support tool integrated with existing corrosion-management practices, with significant changes in treatment conditions subject to appropriate engineering and operational review.

6.7. AI-ASSISTED DEVELOPMENT OF GREEN CORROSION INHIBITORS

AI provides an emerging opportunity to accelerate the development of environmentally preferable corrosion inhibitors. Plant extracts, biomolecules, amino acids, natural polymers, and other renewable materials may contain multiple potentially active constituents, making conventional screening and formulation optimization challenging.

ML can potentially relate molecular descriptors or chemical composition to inhibition efficiency and assist in identifying promising compounds. AI can also support the optimization of extraction conditions, formulation composition, inhibitor concentration, and combinations of active compounds. Toor [26] discussed the potential of AI and ML for accelerating the screening and development of environmentally sustainable corrosion inhibitors. However, the classification of an inhibitor as "green" should not be based solely on its natural origin. Candidate inhibitors should also be assessed for toxicity, biodegradability, thermal stability, chemical compatibility, partitioning behaviour, and corrosion-protection performance under representative oilfield conditions. Future research should therefore develop multi-objective AI models capable of considering corrosion protection together with environmental and operational requirements.

6.8. FUTURE RESEARCH DIRECTIONS

Future research should focus on developing AI systems that are more reliable, transferable, interpretable, and experimentally validated for corrosion-inhibitor applications. One important priority is the development of standardized, high-quality, time-dependent datasets containing both molecular and experimental information. Datasets of this type would help to compare ML algorithms more reliably and improve the reproducibility of models.

Another important direction is merging machine learning with computational chemistry and corrosion science. QSAR modelling in synergy with DFT, MD, electrochemical measurements and experimental corrosion data offers an indirect approach to fully elucidate the inhibitor behaviour. More sophisticated and, in principle, hybrid approaches could enhance the capacity of AI models to connect molecular structure and adsorption behaviour with inhibition performance [11, 26].

Physics-informed and mechanistically constrained ML models are also needed for investigating inhibitor applications in future studies. Such models could be augmented with known relationships, even if not entirely statistically-driven, to account for phenomena such as adsorption, electrochemical kinetics, mass transfer and corrosion reactions. This approach may improve prediction reliability when AI models are applied to conditions outside the original experimental dataset.

Long-term field validation should also become a major research priority. Most published AI-based inhibitor studies are still based primarily on laboratory or curated datasets. Field studies involving continuous corrosion monitoring, inhibitor-residual measurements, changing production conditions, and actual chemical-injection histories would provide stronger evidence of model performance under realistic operating conditions.

Finally, future research should investigate adaptive AI-based inhibitor-management systems capable of updating their predictions as new corrosion and treatment data become available. Such systems could integrate inhibitor selection, performance prediction, dosage optimization, and monitoring within a common decision-support framework. However, automated treatment changes should remain subject to uncertainty assessment, engineering constraints, and human verification until sufficient field evidence demonstrates their reliability.

6.9. CONCLUDING PERSPECTIVE

AI has demonstrated considerable potential for improving corrosion-inhibitor applications in oil and gas facilities, particularly in inhibitor-performance prediction, inhibitor selection, dosage optimization, molecular screening, and treatment monitoring. Nevertheless, the effectiveness of these approaches depends strongly on the quality and representativeness of the underlying data and on the ability of the models to generalize across different inhibitor chemistries and corrosion environments.

The future development of AI-based corrosion-inhibitor management should therefore focus not only on developing more sophisticated algorithms but also on improving experimental data quality, standardization, interpretability, uncertainty

assessment, and field validation. The integration of ML with QSAR, DFT, MD, electrochemical measurements, and corrosion-mechanism knowledge offers a promising pathway toward more reliable inhibitor prediction and design. Ultimately, AI is most appropriately positioned as a decision-support technology that complements experimental qualification, corrosion monitoring, field evaluation, and established corrosion-engineering practice.

7. CONCLUSION

Artificial intelligence (AI) and machine learning (ML) are emerging as useful decision-support tools for corrosion-inhibitor management in oil and gas facilities. The reviewed literature demonstrates applications in corrosion-rate prediction, inhibitor selection, inhibition-efficiency prediction, dosage optimization, molecular screening, environmentally preferable inhibitor development, and interpretation of corrosion-monitoring data. However, the maturity of these applications varies, and most published evidence remains based on laboratory, pilot, or bounded datasets rather than long-term field deployment.

The application of AI to corrosion-inhibitor development is particularly promising when machine learning is combined with experimental corrosion measurements and computational techniques such as quantitative structure–activity relationship (QSAR) modelling, density functional theory (DFT), and molecular dynamics (MD). Such integration can support the identification and prioritization of potential inhibitor molecules while reducing the experimental search space. Similarly, AI-based predictive models can support inhibitor dosage optimization by relating treatment conditions to corrosion response and operating variables. However, AI predictions should complement rather than replace laboratory qualification, corrosion monitoring, field testing, and established corrosion-engineering practices.

A key take-home finding from the analyzed literature is that success in deploying AI to predict PCO at corrosion-inhibitor applications hinges on both quality and diversity of available data. Variations in the chemistry of the inhibitors, metallurgy, composition of electrolyte, temperature conditions, pressure exposure duration, any measurement methods and operating conditions may make mathematical transfer between corrosion systems limited. Given this context, the creation of high-quality corrosion-inhibitor datasets that can be standardized and measured over time is critical to improve the reproducibility, reliability, and generalization of models.

Future progress relies very heavily on more interpretable, uncertainty-quantified, and experimentally validated AI models. Greater integration of machine learning with corrosion mechanisms, electrochemical measurements, QSAR, DFT, MD, and realistic oilfield datasets could improve the reliability of AI predictions under complex operating conditions. Long-term field validation will also be required to determine whether laboratory-developed models can provide reliable decision support for actual inhibitor selection, monitoring, and dosage-management systems. Overall, AI should presently be regarded as a decision-support technology rather than a complete replacement for conventional corrosion-inhibitor engineering. Its greatest value lies in combining large and diverse datasets, identifying complex relationships, accelerating inhibitor screening, supporting treatment optimization, and providing additional information for engineering decisions. With improved datasets, mechanistic integration, experimental validation, and appropriate engineering oversight, AI has the potential to contribute significantly to more efficient, reliable, and sustainable corrosion-inhibitor management in oil and gas facilities.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest concerning the publishing of the review paper.

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